# ESSAYS ON SOCIAL MEDIA, POLITICS AND MISINFORMATION

BY

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## **ABSTRACT**

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## POLITICS AND MISINFORMATION

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False and misleading information flourish on the internet, and in particular on social media sites. In this multi-paper dissertation, I explore why false information spreads on social media sites and how this may affect outcomes such as political knowledge. First, I conduct a quantitative analysis that tests how social media use influences political knowledge in Turkey. Next, I present a qualitative study and provide in-depth qualitative and computational analyses of two partisan clusters on Twitter in Turkey. Finally, I examine the effect of being angry and participating in echo-chambers on sharing behavior using two lab experiments; one conducted in Turkey and another one conducted in the United Kingdom. I find that while generic internet usage is associated with being informed, social media usage is linked to being misinformed. Furthermore, I find that before important events such as elections, members of partisan clusters on social media become very polarized and emotional, which may lead to a less attentive sharing behavior. Finally, I demonstrate that while hypothetical echo-chambers increase the willingness to share false news, being told about the attitudes of another participant in a real social media environment reduces the sharing of false information.

**Keywords:** misinformation, disinformation, echo-chambers, political knowledge, experiments, computational social science

## ÖZET

## SOSYAL MEDYA, SİYASET VE YANLIŞ BİLGİ ÜZERİNE MAKALELER

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Yanlış ve aldatıcı bilgiler başta sosyal medya siteleri olmak üzere internette kolaylıkla yayılmaktadır. Üç farklı makaleden oluşan bu tez çalışmasında, yanlış bilginin sosyal medya sitelerinde yayılması ve bu durumun siyasi bilgiye olan etkisi incelenmektedir. Bu doğrultuda öncelikle niceliksel bir analiz yürütülerek, Türkiye'de sosyal medya ve internet kullanımının siyasi bilgiye olan etkisi incelenmiştir. İkinci olarak, dijital etnografik yöntemler ve bilişimsel sosyal bilim teknikleri kullanılarak Türkiye'de Twitter'da aktif olan iki partizan yankı odası analiz edilmiştir. Son olarak, Türkiye ve İngiltere'de gerçekleştirilen iki farklı laboratuvar deneyiyle öfke ve yankı odalarının yanlış bilgi paylaşımına etkisi mercek altına alınmıştır. Türkiye'de genel olarak internet kullanımının siyasetle ilgili doğru bilgi; sosyal medya kullanımının ise yanlış bilgi dağarcığına sahip olmayla pozitif ilişkili olduğu görülmektedir. İkinci olarak, yankı odalarında aktif rol alan partizan sosyal medya kullanıcılarının seçimler gibi önemli olaylar öncesi çok aktif, polarize ve duygusal oldukları ve bu durumun da daha dikkatsiz paylaşım davranışına yol açabildiği gözlenmiştir. Son olarak, farazi yankı odaları yanlış bilgi paylaşma isteğini arttırırken, gerçek sosyal medya ortamlarında kişiler iletişime geçecekleri diğer kişilerin tutumları hakkında bilgi sahibi olduklarında yanlış bilgi paylaşma oranının azaldığı görülmektedir.

**Anahtar kelimeler:** yanlış bilgi, dezenformasyon, yankı odaları, siyasi bilgi, deney, bilişimsel sosyal bilimler

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## **Chapter 1— Introduction**

## I. Misinformation, Disinformation, and the Internet

False and misleading information flourish on the internet, and in particular on social media sites. Users of popular social networking platforms such as Facebook and Twitter do not have to go through any verification process before disseminating content, and are thus free to share rumors, false news and conspiracy theories with their friends and followers (Del Vicario et al., 2016a; Bessi et al., 2016; Guess et al., 2018; Allcott and Gentzkow, 2017; Törnberg, 2018; Bronstein et al., 2019; Vosoughi et al., 2018). This poses a problem for democracies, as a growing number of people use the internet to access information and to form opinions about political alternatives (Newman et al., 2018).

Misinformation occurs when a piece of false information is produced or shared without the intention to deceive, whereas disinformation involves sharing and producing content with deceptive intentions, for example with the aim of manipulating voters. There are several examples of how mis- and disinformation has spread online and caused substantial damage. One such example comes from the 2016 US Presidential election, where Russian operatives are suspected to have influenced voters by sharing misleading information (Bradshaw and Howard, 2017; Howard et al., 2017). Another example comes from India, where violent mob attacks were incited using unsubstantiated rumors on social media (Pokharel and Griffiths, 2018). Finally, conspiracy theories that have proliferated on social media sites and blogs have made concerned parents unwilling to vaccinate their children (Smith and Graham, 2019).

<sup>&</sup>lt;sup>1</sup> Another type of potentially harmful information is known as 'malinformation', which refers to a situation where some correct information is taken out of context and used to deceive people (Wardle and Derakhshan, 2017).

While we have documented the existence of certain types of mis/disinformation (Wardle and Derakhshan, 2017; Guess et al., 2018; Del Vicario et al., 2016a& 2016b; Vosoughi et al., 2018; Törnberg, 2018), we do not fully understand the many causes and implications of the spread of false and misleading content on social media. It is, for example, not yet clear *why* people share misleading content or *why* people read misleading articles. Is it because they are angry, or are they motivated by other factors? Further, we do not know the extent to which false information actually influences peoples' perceptions, opinions, and actions. Finally, while studies conducted in the early 2000s found positive associations between using online news sources and political knowledge (Kenski and Stroud, 2006; Bimber and Davis, 2003; Drew and Weaver, 2006; Reuter and Szakonyi, 2013), it is possible that the popularity of social media has altered this association.

In this multi-paper dissertation, I explore why false information spreads on social media sites and how this may affect outcomes such as political knowledge. In the second chapter, I conduct a quantitative analysis that tests how social media use influences political knowledge in Turkey. Next, I present a qualitative study and provide an in-depth qualitative analysis of two partisan 'clusters' on Twitter in Turkey. Finally, I examine sharing behavior using two lab experiments; one conducted in Turkey and one conducted in the United Kingdom. The final chapter concludes by discussing the main findings, shortcomings, and presents avenues for future research.

## II. Mis- and Disinformation in Political Theory

While the advent of social media has brought the problem of mis- and disinformation to the fore, it must be said that it is a topic that has garnered interest for some time. Having an informed citizenry has, for example, long been an important element within democratic theory, as citizens are tasked with electing and removing officials from office.

Citizens are, however, rarely as informed as one might hope (Delli Carpini and Keeter, 1996). Plato was, for this reason, not keen on leaving the governance of cities to the 'common man'. They were, in his eyes, interested in bodily pleasures at the expense of the truth:

"... he lives from day to day indulging the appetite of the hour; and sometimes he is lapped in drink and strains of the flute; then he becomes a water-drinker, and tries to get thin; then he takes a turn at gymnastics; sometimes idling and neglecting everything, then once more living the life of a philosopher; often he is busy with politics, and starts to his feet and says and does whatever comes into his head... Let him then be set over against democracy; he may truly be called the democratic man." (Republic, Book XIII, 196)

Plato only trusted 'philosopher kings'—men who pursued the truth rather than worldly pleasures—to govern the state. In *Politics*, Aristotle expresses his concern about the ability of ordinary individuals to rule as they do not have sufficient merits. Moreover, in *Considerations of Representative Government*, J.S. Mill (1861) argues for a voting system that allocated multiple votes to the educated elite while giving fewer votes to the masses.

Having an informed citizenry is also central in modern democratic theory. Dahl (1989: 38), for example, listed an "enlightened understanding" as a criterion for democracy. This is important because, as Rapeli (2014: 25) states "The self-governing citizen is expected to make choices between politicians and policies, and those choices are expected to be an expression of individual or group interests."

While citizen knowledge is vital for democratic governance, we also know that few citizens are sufficiently well informed (Delli Carpini and Keeter, 1993 & 1996). The lack of citizen knowledge has become one of the main criticisms of democracies (Lippmann, 1922). This lack of knowledge is, according to Downs (1957), mainly due to poor incentives; voters do not bother to inform themselves, as their vote has an infinitesimal impact on their lives.

Nevertheless, some posit that voters can make rational decisions with low levels of information or through the use of heuristics and shortcuts. Popkin (1994), for instance, argues that voters can make rational political decisions with the low levels of information that they gather from a variety of sources such as the media and their network. In the absence of an unlimited attention span, humans choose to focus on information that is worth learning (Lupia and McCubbins, 1998). Social media might, however, alter how well these heuristics work, if people become overly exposed to false information and are unable (or lack the time and desire) to distinguish between high- and low-quality sources of information.

## III. The Internet: Home to both Knowledge and Falsehoods

The studies contained in this dissertation are set in a context where people are inundated with information—political and otherwise. The contemporary information environment is often defined as chaotic (Waisborg, 2018) or as a disorder (Wardle and Derakshan, 2017). Individuals have access to an excess amount of information—of both high and low quality—and have to decide what they want to consume to inform themselves. In today's 24-hour news cycle everyone can effortlessly and cheaply follow political developments on their smartphones, and access articles on demand. Social media has also made it increasingly easy to share content with friends and followers.

The internet was for a long time considered to have an unambiguously positive influence on society, with scholars arguing that it would increase political knowledge, awareness, and participation (Bimber and Davis, 2003; Kenski and Stroud, 2006). This view has, however, become more nuanced with time, with many now recognizing that internet use can lead to erroneous beliefs and misperceptions.

In particular, many voiced their pessimism about the effects of online platforms after the 2016 US Presidential elections, during which Russian operatives are thought to have run a

disinformation campaign on social media. There have now even been calls for governments to regulate social media companies in order to avoid this type of interference in the future (Solomone, 2018). Scholars have also documented how social media sites have become hosts of substantial amounts of mis- and disinformation (Vosoughi et al., 2018; Guess et al., 2018; Del Vicario et al., 2016; Törnberg, 2018).

The absence of regulators or editorial gate-keepers, combined with the excessive availability of information, means that individuals may depend on partisan cues or shortcuts when choosing which content to consume. Further, the algorithmic structure of social media platforms promotes the formation of echo-chambers, where individuals get exposed to like-minded information and opinions (Sunstein, 2001). Content that individuals are exposed to in echo-chambers may seem more trustworthy, as it is coming from people with similar points of view, and as it is likely to have been shared many times. In sum, there are several components of the current social media environment that could affect outcomes such as polarization and political knowledge.

## IV. The Aim and Structure of this Dissertation

While several hypotheses have been formulated regarding how false content is shared and perceived, we do not yet know for certain how individuals are influenced by, and make decisions in, online environments. For example, are their decisions influenced by their emotional state? Are people more likely to share controversial content in like-minded environments? In this dissertation, I aim to empirically answer such questions using a mixed-methods approach that involves participant observation, quantitative analyses, and lab experiments. More specifically, I set out to answer the following two research questions:

- 1. What are the causes and implications of mis- and disinformation?
- 2. Why do people believe and share false information online?

In the next chapter, I examine whether using online platforms is linked to political knowledge. In order to do so, I analyze nationally representative survey data collected in Turkey in 2015. I find that social media usage is associated with being misinformed, I also, however, find that internet usage is positively associated with being informed about politics. This chapter provides a better understanding of the political implications of mis- and disinformation on social media.

In the third chapter, I present an in-depth analysis of echo-chambers on Twitter. I create two echo-chambers—one that is pro-government and one that is anti-government—on two separate Twitter accounts. I conduct a covert participant observation of these hyper-partisan clusters prior to the 2017 referendum in Turkey. I support my observations using computational analyses of tweets and networks. I find that before important events such as elections, members of partisan clusters on social media become very active, polarized, and emotional, which may lead to a less attentive sharing behavior. Many users trust their network members and share inaccurate information, false news and unverified rumors. The sharing behavior intensifies during politically significant and emotional events.

In the fourth chapter, I test whether being angry and participating in an echo-chamber affects how people share false news. As many users I had observed in the third chapter were demonstrating anger, I wanted to understand the effect of this emotion on the perceptions regarding—and sharing of—false news. I also wanted to test whether echo-chambers constitute fertile ground for the diffusion of false news. In order to do so, I conduct two lab experiments—one in Turkey and one in the UK. In the first experiment, which was conducted in Turkey, I induced anger through 'autobiographical recall', after which the participants were asked to read a fabricated news article. They were then asked to imagine a social media group composed of participants who support either the AK Party, CHP, or no party at all. Finally, they were asked whether they would be willing to share the article that they read with this group.

In the second experiment, which was carried out in the UK, half of the participants were first asked to write about a personal and political memory that made them angry. All participants were asked to read a false news article about immigration and were then assigned to chat groups. They were randomly placed into groups that were either told, or not told, about the political alignment of the other chat group participant. The main outcome of interest in this experiment is whether or not the individuals discussed and shared information about the articles in the chat groups.

These experiments produced a number of noteworthy results. First, the anger treatment did not have any significant effects on my outcomes of interest. This may, however, be due to a failure to successfully induce anger among the participants, rather than due to anger being ineffective per se. Second, the echo-chamber treatments had nuanced effects. In the first experiment, where I measured the willingness to share a false news article, those assigned to like-minded social media groups indicated a greater willingness to share the article. In the second experiment, being told about the attitudes of the other participant in a real chat environment reduced the sharing of false information. This effect was mainly driven by the cross-cutting chat groups, where the participants were assigned to chat groups with others who did not share their attitudes on immigration.

The final chapter concludes by summarizing the main findings and discussing ideas for future research.

## Chapter 2 – (Mis)information and The Internet: Evidence from Turkey

## I. INTRODUCTION

An increasing number of people rely on the internet as a source of political information. This development may affect political knowledge, as there are substantial differences between the internet and other sources of information. The internet provides users with opportunities to produce and disseminate material without requiring the approval of publishers or editorial boards. It also presents people with new fora where they can exchange opinions and access the latest news.

The internet may facilitate the spread of misinformation, which can occur through the dissemination of rumors, false news, conspiracy theories, and hoaxes (Bessi et al., 2016). Several studies have sought to understand the presence of misinformation on the internet, with a particular focus on social media (Chen and Sin, 2013; Starbird et al., 2014; Friggeri et al., 2014; Del Vicario et al., 2016; Allcott and Gentzkow, 2017). So-called echo-chambers—clusters of likeminded people on social media sites—have been identified as fertile ground for the spread of false information (Del Vicario et al., 2016a). The internet may, however, also increase political knowledge by giving voters access to a substantial amounts of quality content (Bimber and Davis, 2003; Xenos and Moy, 2007; Kenski and Stroud, 2006).

There are thus several opposing forces at play, and it is not yet clear what the net effect of internet use—and more specifically social media use—is on voters' political knowledge. I aim to contribute to this literature by examining the relationship between internet use and being informed, uninformed, and misinformed. While several studies focus on demonstrating the existence of malicious content online (see Vosoughi et al, 2018; Del Vicario et al., 2016a &

2016b; Törnberg, 2018 among others), there are not many studies that show how false online content affects peoples' political knowledge. I address this gap by analyzing data from the 2015 Turkish Election Survey.

I find that social media use is associated with higher levels of misinformation. I also find that internet use is positively associated with political knowledge. These findings are, to some extent, in line with previous studies that highlight how actors use social media to spread propaganda and misinformation, while simultaneously not contradicting studies which argue that internet access increases political knowledge. It is, however, not possible to provide a clear causal interpretation of these associations. Further research should be conducted to increase our understanding of the mechanisms underlying the results.

This chapter is structured as follows. Section II gives an overview of the literature on political knowledge and its relationship with internet use; Section III discusses the political and media environments in Turkey; Section IV presents our research questions and hypotheses; Section V describes the data used in the study, and Section VI contains the quantitative analysis. Section VII concludes the article.

## II. Political Knowledge and the Internet

## A. The Role of Political Knowledge

Citizens of representative democracies require information about political alternatives in order to vote for the party, candidate, or policy option that best aligns with their interests (Berelson, 1952; Dahl, 1989). Authoritarian regimes, on the other hand, constrain media freedoms in order to hinder citizens from accessing information that is damaging to the regime.

Berelson, Lazarfeld and McPhee (1954: 308) state that:

"The democratic citizen is expected to be well informed about political affairs. He is supposed to know what the issues are, what their history is, what the relevant facts are, what alternatives are proposed, what the party stands for, what the likely consequences are."

Political knowledge is an important variable in democratic theory. For instance, knowledge of political principles and institutions is associated with support for democratic principles (Galston, 2001). Political knowledge, as an independent variable, is a predictor of political engagement while poorly informed voters are known to be less able to follow discussions of public issues and are less interested in political participation (Popkin and Dimock, 1999; Delli Carpini and Keeter, 1996; Neuman, 1986; Verba et al., 1997). As several scholars acknowledge, though, the citizen is neither highly informed nor "does he avoid a certain misperception of the political situation when it is to his psychological advantage to do so." (Berelson, Lazarsfeld and McPhee, 1954: 308)

Being informed entails having factual and accurate beliefs. Somebody who does not hold any factual beliefs is uninformed. Whereas if they hold incorrect beliefs, then they are not "just in the dark, but wrongheaded" (Kuklinski et al., 2000, pg. 793). Delli, Carpini and Keeter (1996) argue that being misinformed is different from being uninformed.

Being misinformed can both be a result of receiving faulty information and a result of incorrectly processing correct information. To be uninformed, on the other hand, means that there was no prior exposure to information. Mondak (1999) posits that there are four levels of knowledge: 1) fully informed, 2) partially informed, 3) misinformed, and 4) uninformed.

Distinguishing between what is correct and incorrect may be more difficult online, as individuals often encounter unreliable and partisan information that caters to their political biases. The following section expounds on the potentially positive and negative effects of internet use on political knowledge.

## B. Internet Use and Political Knowledge

It is insufficient to look at whether internet use affects the level or share of correct knowledge, as there may be a simultaneous process that affects the acquisition of both correct and incorrect

information. One might, for instance, become less uninformed while simultaneously becoming more informed *and* misinformed.

Several studies have looked at the relationship between internet use and political knowledge. For instance, Reuter and Szakonyi (2013) investigate the relationship between social networking sites and the understanding of electoral fraud in Russia. They show that Facebook and Twitter use increases political awareness. Drew and Weaver (2006) report that there is a positive relationship between online news exposure and knowledge of political issues in the US. Using a dataset from 2000, Kenski and Stroud (2006) find that there is a positive association between internet use and political knowledge. Additionally, Xenos and Moy (2007) show that there is a positive relationship between internet use and the acquisition of political information using data from the American National Election Survey. Furthermore, consuming online news may affect levels of factual political knowledge (Beam et al. 2016).

The internet might also increase the political knowledge of voters in specific fields as Baum and Groeling (2008: 346-347) underline that "... one clear manner in which the Internet appears to differ from other mass media is the degree of niche targeting of political information-oriented Web sites." For instance, Bimber and Davis (2003) demonstrate that those that visit political candidates' web sites have more political knowledge than those that do not.

However, Groshek and Dimitrova (2011) suggest that there is no evidence of positive effects of Web 2.0-type applications and internet use on voter learning. Richey and Zhu (2015) find no connection between internet access and political knowledge. Kaufhold, Valenzuela and Gil de Zuniga (2010) demonstrate that those who consume online citizen journalism had lower levels of political knowledge than those who follow professional news outlets. Moreover, Dimitrova et al. (2014:110) reveal that while "the use of some online news sites leads to higher levels of political knowledge, party web sites and social media do not." In sum, the bulk of the studies above find a positive relationship between some aspects of internet use and political

knowledge, however, given the complexities of the internet as a communication platform, it is still uncertain what the net effect is.

## C. Internet use and Misinformation

The internet has the potential to change democratic practices through online features that make the flow of information fast and cheap, as well as by facilitating deliberation (Dahlberg, 2001). However, it can also become a tool that increases political misperceptions due to features that enable the creation of echo-chambers and the effective dissemination of false information.

A characteristic that differentiates the internet from other sources of political information is its accessibility. Today, it is much easier and cheaper to produce, and access political information (Flaxman et al., 2016). Especially on social media sites such as Facebook and Twitter, users can easily share their preferred content with their network (Bakshy et al. 2012). Furthermore, as Flaxman et al. (2016: 299) point out "search engines facilitate a diversity of voices by offering access to a range of opinions far broader than those found in one's local paper, greatly expanding the information available to citizens and their choices over news outlets."

Given that voters have internet access, they can look for information any time they want. This ease of access might increase the likelihood of being exposed to political news. However, this increased likelihood of exposure to political news also bring out the possibility that citizens will expose themselves to low-quality news sites or social media sites which facilitate the dissemination of false news and propaganda (Sanders, 2016).

Internet users can relatively easily find news sources that cover topics in which they are interested. As Allcott and Gentzkow (2017: 211) argue, "Content can be relayed among users with no significant third-party filtering, fact-checking, or editorial judgment. An individual user with no track record or reputation can in some cases reach as many readers as Fox News, CNN, or the New York Times". Social media facilitates the dissemination of

information to thousands—or even millions—of people without any editorial gatekeeping or other mechanisms that can confirm the veracity of content (Zollo et al., 2015; Allcott and Gentzkow, 2017). Social media has also drastically reduced the costs of disseminating false news (Carson, 2017). This cost reduction facilitated the flow of rumors, fake news, and hoaxes on social media sites (Bessi et al., 2016).

Users might be subject to false information on their topic of interest. Without the skills to differentiate correct from incorrect information, they might believe in what they read even if it includes incorrect information. Several factors, ranging from cognitive abilities, partisan sensitivities and prior exposure may play a role in people's susceptibility to false news and other types of false information (Dechêne et al., 2010; Pennycook et al., 2018; Pennycook and Rand, 2018).

Moreover, as Prior (2005) argues, the internet can serve as a distraction to many users who are more interested in entertainment than in political information. Internet use might, therefore, reduce the level of political knowledge, as people spend less time on traditional media (for example, television) where the unintended exposure to news can occur more readily (Sunstein, 2001). There is, however, also research suggesting that accidental exposure to news takes place on social media and affects people's online political participation (Valeriani and Vaccari, 2016).

### D. Internet use and Partisanship

The internet allows voters to consume news from websites that confirm their political bias.

Users can, as a result of customization options, easily ignore content that challenges their political stances, and may thereby become less informed.

Sunstein (2001) argues that selective exposure to congruent information increases polarization. The more partisan citizens become, the more they might visit unreliable and partisan websites. Moreover, social media algorithms, such as the one used on Facebook,

facilitate this process by showing what users want to see (Sunstein, 2018). Previous research on Twitter reveals that social media users in the US follow politicians and individuals that confirm their political dispositions (Haberstam and Knight, 2016). Gaines and Mondak (2009) show that there is a marginal tendency for clustering on online social networks between ideologically similar students. Another study finds that people with similar political views are more likely to be linked on Facebook (Gilbert and Karahalios, 2009). Other research supports these findings by demonstrating the existence of highly segregated political clusters on Twitter (Conover et al., 2011; Rainie and Smith, 2012). Confirmation bias and partisanship might, therefore, affect what users end up reading, how they interpret content, and consequently, their level of misinformation on political issues (Kumar and Shah, 2018).

Echo-chambers on social media sites enable the fast and often unhindered circulation of incorrect information (Tüfekçi, 2016; Del Vicario et al. 2016b; Howard et al., 2017). False news, rumors, conspiracy theories, as well as hoaxes disseminate quickly via echo-chambers (Bessi et al., 2016). For example, Vosoughi et al. (2018) demonstrate that false rumors spread faster and more in volume than correct content on Twitter. Del Vicario et al. (2016b) present that Facebook users selectively expose themselves to incorrect content and spread conspiracy theories using various public pages while generating echo-chambers. Moreover, the same study reveals that there are social media trolls who intentionally spread incorrect information. Individuals who use social media sites might, therefore, become misinformed.

For example, after the 2016 elections in the US, many scholars and pundits emphasized the effect of fake news on the election. Silverman (2016) shows that the most popular false news stories were shared more than the most popular mainstream news stories. Moreover, most traffic to false news web sites comes from social media sites (Allcott and Gentzkow, 2017: 222). As several scholars (Bradshaw and Howard, 2017; Ferrara et al., 2016) demonstrate,

political bots, occasionally employed by governments around the world, can contribute to the manipulation of information on social media.

Moreover, the internet facilitates interactions between different users. This interaction most commonly takes place in social media networks such as Facebook and Twitter. These platforms serve as sources where people get their political news by following news outlets or individuals such as journalists, opinion leaders, politicians, and other users. Homogenous communities on social media might be accelerating the diffusion of incorrect information, especially during crisis periods (Starbird et al., 2014). For example, Kwak et al. (2010) argue that 50% of retweets are shared in the first hour after a tweet is posted in a crisis. Chen and Sin (2013: 1) posit that not only crises but other factors such as personality traits affect the sharing of incorrect information. While this is the case, social media users occasionally intervene to correct incorrect information, such as rumors, shared by other social media users (Mendoza et al., 2010).

As this review demonstrates, internet access does not automatically translate into a more informed or misinformed citizenry. The choice-laden structure of the internet and the effect of algorithms (Tüfekçi, 2016; Sunstein, 2018), the availability of internet access, the quality of online content and the personal qualities of users (Chen and Sin, 2013) and the short format of social media feeds (Allcott and Gentzkow, 2017) can affect the way that the internet and social media influence what voters know about politics. While the majority of recent studies focus on detecting and correcting misinformation on the internet, several studies find links between internet usage and increased political knowledge. As Tucker et al. (2018) underline, we are in the dark about the effects of using social media on political outcomes. This study fills a gap by providing supporting survey evidence of the association between using both the internet and social media and political knowledge.

## III. The Turkish Case

## A. Media in Turkey

Even though the Turkish press has never been entirely free (Bayram, 2010), the AKP era has brought about even more criticism and questions about press freedoms (Çarkoğlu, Baruh, Yıldırım, 2014). Reporters Without Borders (2019) ranks Turkey 157th out of 180 countries and Freedom House (2016) started classifying Turkey as "Not Free" since 2016 in terms of internet freedoms.

The liberalization process of the Turkish media mostly took place between the 1980s and 90s. By the end of this period, major businesses owned various media outlets in Turkey. More business groups, mostly pro-government, started owning media companies in the 2000s (Christensen, 2007; Finkel, 2000; Çarkoğlu et al., 2014). Reflecting the government's influence on the Turkish media, there have been cases in which several different newspapers ran the same headline vocalizing the government's interests (Yılmaz, 2016). The Turkish media, overall, has been influenced by the economic relations between the business owners and the government (Somer, 2010).

The internet can serve as an alternative to biased traditional media outlets. The internet was only available to 55.9% of the population in 2015 (TUIK, 2016). Even though internet access is not as widespread as the access to traditional media, 87% of adult internet users (or those who report having smartphones) in Turkey claim that they use social media, making Turkey among the top five emerging countries in terms of social media usage (Poushter, 2016).

There are various online news portals, such as Diken.com that go against state discourse. Social media is also a prominent news source—and has been since the 2013 Gezi Park Protests (Haciyakupoğlu and Zhang, 2015). During the Gezi protests, traditional media, including major news channels like CNN Turkey, failed to cover the protests, which led to a decline in peoples' trust of these outlets (Hutchinson, 2013). In 2018, around 38% of online

population trusted traditional news sources, while 33% trusted social media as a news source (Yanatma, 2018).

It is important to note, however, that social media is not free of government intervention. Both through censorship and manipulation with social media trolls, the government attempts to control social networking sites such as Facebook and Twitter. Turkey has also banned access to these platforms on various occasions (Freedom House, 2016). The government interferes with individual posts on social media and requires that these sites remove undesired content by issuing court orders. With 2071 requests in 2015 alone, Turkey has become the leading country in terms of Twitter content removal requests (Turkey and Facts, 2016; Twitter Transparency Report 2016). Moreover, the government employs 'trolls' in order to control the agenda on social media platforms (Kızılkaya, 2015). These trolls create and promote pro-government hashtags daily in addition to insulting and intimidating opposition journalists.

Overall, the mainstream media in Turkey is heavily censored and biased towards the governing party. Social media sites provide an alternative to access anti-government news and opinions. However, social media sites are also manipulated by pro and anti-government social media trolls and other actors (which are discussed in detail in the next chapter).

## B. The 2015 Election Cycle

Turkey has held four elections between March 2014 and November 2015. This paper uses data from the period running up to the general election on June 2015. The ruling Justice and Development Party won all three consecutive general elections in 2002, 2007 and 2011, thereby its vote share went from 34% to 50% during this period (Çarkoğlu & Yıldırım, 2015). The June 2015 elections, however, resulted in a loss of 10% of the votes for the AK Party, leading to a failure to form a government.

Although there are no comprehensive content analyses that clearly demonstrate the state of the Turkish media during this the campaign period, Çarkoğlu and Yıldırım (2015, pg. 60) argue that "a casual observer gets from the 2015 election campaign is that President-elect Recep Tayyip Erdoğan actively campaigned for the AK Party and openly criticized the three major opposing parties and their leaders" even though the constitution of Turkey prohibited it.

Turkey constitutes a significant case to study the effect of internet use and social media on political knowledge. The internet provides an alternative to traditional media, which is heavily influenced by state discourse during election periods in Turkey. Social media usage is high among internet users. Nevertheless, it still has the potential to misinform voters. Finally, Turkey is an understudied case in social media studies, and as Tucker et al. (2018) implicate, it is crucial to expand the geographical focus of social media research.

## IV. Research Questions and Hypotheses

In light of the previous literature on the subject, I ask the following research questions in this study:

- **RQ1.** How does internet use affect peoples' level of correct, as well as incorrect, knowledge about politics in Turkey?
- **RQ2.** How does social media use affect peoples' level of correct, as well as incorrect, knowledge about politics in Turkey?

Following the research questions above, I therefore test the following hypotheses:

H<sub>1</sub>: Internet use has a positive effect on political knowledge

H<sub>2</sub>: Among people that use the internet, those that rely on social media are more likely to be misinformed than those that do not

H<sub>3</sub>: Among people that use the internet, those that are partisan are more likely to be misinformed

H<sub>4</sub>: Among people that use the internet, those that are partisan are less likely to be uninformed

## V. The Turkish Election Survey

The Turkish Election Survey (TES 2015) consists of a three-wave panel and two nationally representative cross-sectional samples. The first survey that I am using includes interviews that were done face-to-face with 2201 participants from 49 provinces. Fieldwork was carried out between 19 March and 26 April 2015. The sampling procedure started with the Turkish Statistical Institute's (TUIK) NUTS-2 regions which include the 26 sub-regions in Turkey. Participants were selected randomly from the Address Based Population Registration System. Based on TUIK's block data, which was set at a block size of 400 residents, a probability proportionate to size sampling was applied in assigning the blocks to NUTS-2 regions. The interviewed individuals were selected through a lottery method which took the registered target population of 18 years or older in each household.<sup>2</sup>

The survey includes several questions that allow me to test my hypotheses. I use questions measuring internet access, using social media as an online activity as well as more general questions measuring age, level of education, interest in politics, and gender.

The primary dependent variable in this paper is political knowledge. The measurement of political knowledge is a contested issue. Scholars express concerns over the content validity of the test items in surveys. Neuman (1986: 186) underline that items for measuring political knowledge should include: the components of government, its core values (i.e. "separation of powers") and its essential features such as the party system. I use eight questions in the Turkish Election Study to measure political knowledge, which is in line with these recommendations.

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<sup>&</sup>lt;sup>2</sup> Koç University, Center for Survey Research. Official website: <a href="https://csr.ku.edu.tr/public-opinion">https://csr.ku.edu.tr/public-opinion</a>

The survey includes questions measuring respondents' knowledge on the authority and responsibilities of the president, constitutional reforms and the electoral system in Turkey as well as a general question about separation of powers in democracies and another question about whether or not the majority of democracies have a parliamentarian system. The respondents are presented with statements about these issues and asked whether or not they think the statement is right or wrong.<sup>3</sup> The answers to the questions are judged on a scale from 1-5 with 1 being definitely wrong and 5 being definitely right. 'Don't know' responses (DKs) are worded as "I am not sure" (3) and No Opinion/No answer.

First, I separate each question into three dummies indicating whether the respondent answered correctly, incorrectly, or said that they do not know (DK). I then sum the total number of correct, incorrect or DK answers for each respondent as three separate variables—total correct, total incorrect, and total DK. I divide these variables by 8 (there are eight questions in total) to get the share of correct, incorrect, and DK answers. I carry out OLS regressions on the shares of correct, incorrect, and DK answers. These OLS estimates constitute the basis of my subsequent analysis.

In order to test  $H_1$ , I use the responses to two questions about internet use as the main independent variables. The first question is, "Do you use the Internet?" (0=never to 6=daily). To test our second hypothesis, I examine the association between political knowledge and the frequency of social media use (coded from 0= never to 6=every day).

As for the third and fourth hypotheses, I examine the relationship between partisanship and political knowledge. The main motivation to do this comes from the literature on motivated reasoning: individuals often make an effort to arrive at conclusions that confirm their biases (Taber and Lodge, 2006). Partisanship may affect the way individuals process information that confirms their beliefs and attitudes (Campbell et al., 1960). They may reject the sources that

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<sup>&</sup>lt;sup>3</sup> The questions and the statements can be found in the Appendix.

provide challenging information, whether it is correct or not. Jerit and Barabas (2012) demonstrate that partisans are more likely to learn positive information about their preferred party, whereas they are also more likely to reject negative information about their party. Those who, for instance, support the governing party may visit websites and follow social media accounts that reflect the government's interests without distinguishing between correct or incorrect information. I, therefore, include partisanship as a control variable in all my models.

I test the relationship between partisanship and political knowledge by creating a binary variable that indicates support for political parties in Turkey. For example, those who say that they are supporters of the Justice and Development Party are coded as 1, while those that do not are assigned 0. Those who did not disclose which party they supported or said they do not support any party are coded as 0 on all party binary variables.

Given that political knowledge is linked to interest in politics and education (Delli Carpini and Keeter, 1993; Mondak, 1999), I will include these in the regressions as control variables. I also control for gender, as women are likely to know less than men as a result of the inequalities in access to knowledge and are less likely to guess in surveys (Mondak, 1999). I control for age as the older people get, the more they are expected to know, and younger people are more likely to use the Internet. I cannot control for income because of the high number of missing values in the dataset, which causes a significant loss of observations. I use living in urban areas as a proxy for income as residents of urban areas are expected to have a higher income than the residents of rural areas. I also control for traditional media consumption (TV and newspaper) as many people use both traditional and new media outlets simultaneously.<sup>4</sup> Some descriptive statistics are provided below:

<sup>&</sup>lt;sup>4</sup> Urban is coded as 0=rural and 1=urban, Gender is coded as 0=male 1=female, Age is "age in years". Traditional media consumption (1=never to 7=everyday).

TABLE A1: DESCRIPTIVE STATISTICS

| VARIABLES                     | Obs  | Mean  | Min | Max  |
|-------------------------------|------|-------|-----|------|
| Share of Correct              | 2201 | 0.34  | 0   | 1    |
| Share of Incorrect            | 2201 | 0.18  | 0   | 0.75 |
| Share of DK                   | 2201 | 0.48  | 0   | 1    |
| Internet                      | 2201 | 2.42  | 0   | 6    |
| Freq. of Using Social Media   | 2200 | 2.04  | 0   | 6    |
| Political interest            | 2193 | 0.62  | 0   | 1    |
| Female                        | 2201 | 0.55  | 0   | 1    |
| Age                           | 2180 | 42.45 | 18  | 91   |
| Freq. of Following Newspapers | 2199 | 3.45  | 1   | 7    |
| Freq. of Following TV         | 2198 | 6.35  | 1   | 7    |
| Urban                         | 2129 | 0.79  | 0   | 1    |
| Education in years            | 2191 | 7.51  | 0   | 15   |
| Partisanship                  | 2201 | 0.69  | 0   | 1    |

Around 55.2% of the sample is composed of female respondents. The mean age in the sample is 42, and the mean level of education is eight years. Around 62% of the participants stated that they are interested in politics, and 69% disclosed that they strongly support a political party in Turkey. Around 43% of respondents stated that they use the internet.

TABLE A2: DESCRIPTIVE STATISTICS ON INTERNET USAGE

| Internet Usage         | Freq. | Percent |
|------------------------|-------|---------|
| Never                  | 1,243 | 56.47   |
| Less than once a month | 9     | 0.41    |
| Once a month           | 16    | 0.73    |
| 2-3 times a month      | 17    | 0.77    |
| Once a week            | 46    | 2.09    |
| 2-3 times a week       | 164   | 7.45    |
| Daily                  | 706   | 32.08   |
| Total                  | 2,201 | 100.00  |

24% of participants in the sample use social media sites like Facebook and Twitter daily (Table A3).

TABLE A3: DESCRIPTIVE STATISTICS ON SOCIAL MEDIA USAGE

| Frequency of Social Media | Freq. | Percent |
|---------------------------|-------|---------|
| Never                     | 1,349 | 61.32   |
| Less than once a month    | 20    | 0.91    |
| Once a month              | 20    | 0.91    |
| 2-3 times a month         | 47    | 2.14    |
| Once a week               | 67    | 3.05    |
| 2-3 times a week          | 172   | 7.82    |
| Daily                     | 525   | 23.86   |
| Total                     | 2,200 | 100.00  |

## VI. Results

## A. Main Analysis

I analyze the effect of our independent variables on the shares of correct, incorrect, and DK answers. To test for H<sub>1</sub> (Internet usage has a positive effect on political knowledge), H2

(Among people that use the internet, those that rely on social media are more likely to be misinformed than those that do not) I carry out regressions to explore the effect of internet and social media use on these three—shares of correct, incorrect, don't know—variables.

In my models, I look at the relationship between internet usage and social media usage and the share of correct, incorrect, and DK answers. I control for political interest, gender, age, education in years, frequency of following political news on TV and newspapers (two variables), living in urban areas, and partisanship.

Table B1 provides the results of the regression analysis on the share of correct, incorrect, and DK answers. There is a statistically significant and positive relationship between internet use and the share of correct answers. As for the analysis of social media usage in the model, those who use the internet have higher shares of correct responses whereas using social media does not produce any statistically significant results holding all else constant. Interestingly, partisanship has no statistically significant relationship with the dependent variable. Female respondents have a lower share of correct answers, whereas age has a positive relationship with being informed. Political interest is also positively associated with political knowledge and is statistically significant on a 99% confidence level—a result which holds across all models. Living in urban areas is positively associated with the share of correct answers. We also observe that following news on TV and newspapers have positive relationships with the share of correct answers. Also, the more educated people are the more correct answers they had.

TABLE B1. OLS ESTIMATES OF SHARE OF CORRECT, INCORRECT AND DK RESPONSES

| VARIABLES  | Correct   | Incorrect | DK        |
|--|-----------|-----------|-----------|
|  |           |           |           |
| Internet access (never to daily)                 | 0.0105**  | -0.0029   | -0.0051   |
|  | (0.004)   | (0.002)   | (0.005)   |
| Frequency of social media usage (never to daily) | 0.0044    | 0.0073**  | -0.0129** |
|  | (0.003)   | (0.002)   | (0.005)   |
| Political interest                               | 0.0810**  | 0.0456**  | -0.1286** |
|  | (0.010)   | (0.008)   | (0.015)   |
| Gender (female=1, male=0)                        | -0.0700** | -0.0373** | 0.1089**  |
|  | (0.010)   | (0.007)   | (0.014)   |
| Age  | 0.0018**  | 0.0005*   | -0.0022** |
|  | (0.000)   | (0.000)   | (0.000)   |
| Education in years                               | 0.0086**  | 0.0038**  | -0.0121** |
|  | (0.001)   | (0.001)   | (0.002)   |
| Frequency of following news on TV                | 0.0111**  | -0,001    | -0.0117** |
|  | (0.003)   | (0.002)   | (0.004)   |
| Frequency of following news on newspapers        | 0.0069**  | 0.0051**  | -0.0126** |
|  | (0.002)   | (0.002)   | (0.003)   |
| Partisanship                                     | 0.0184    | 0.0150*   | -0.0312*  |
|  | (0.010)   | (0.007)   | (0.014)   |
| Living in urban centers                          | 0.0258*   | 0.0064    | -0.0324*  |
|  | (0.011)   | (0.008)   | (0.016)   |
| Constant   | 0.0252    | 0.0902**  | 0.8860**  |
|  | (0.027)   | (0.021)   | (0.040)   |
| Observations                                     | 2,092     | 2,092     | 2,092     |
| R-squared  | 0.254     | 0.129     | 0.261     |

Notes: Robust standard errors in parentheses

The second column shows the results of the regression analysis on the share of incorrect answers. Using the internet does not have a significant relationship with being misinformed when controlling for social media usage, political interest, education, living in urban areas, partisanship, and traditional media consumption. While political interest is positively

associated with more incorrect answers, females have a lower share of incorrect answers compared to males. However, being partisan is positively associated with the share of incorrect answers. My results show that the more time people spend on social media, the higher their share of incorrect answers while holding all else constant. Moreover, being exposed to newspapers for news is positively associated with more incorrect answers. These results indicate that there is a positive relationship between social media and misinformation, providing support for my hypotheses.

Column 3 provides the results for the analysis of the share of DK answers. The relationship between being uninformed, and internet usage, is negative but not statistically significant. Interestingly, the more people use social media, the lower the share of DK answers (99% confidence level). Moreover, political interest has a negative relationship with being uninformed, as well as following news on TV, education, age, and living in urban areas. Females have a higher share of DK answers than males. Partisan respondents also have a lower share of DK answers, which supports my hypothesis.

## VII. Conclusion

More people are getting their political news from online sources, such as social media sites (Pew Research, 2016; Newman et al., 2018). This chapter provides evidence with regards to how using online news sources might affect political knowledge and misinformation, using an electoral survey conducted in Turkey.

The internet has the potential to inform citizens, especially in settings where the media is not entirely independent of political actors. The internet also facilitates misinformation by exposing citizens to false news or propaganda. Previous research shows that fake news and false information, as well as rumors, conspiracy theories and hoaxes spread on social media (Vosoughi et al., 2018; Bessi et al., 2016; Del Vicario et al., 2016a & 2016b).

In this chapter, I used data from the Turkish Election Study conducted in Turkey in 2015. I used responses to eight questions as a proxy for political knowledge and created variables that for each respondent show what share of the answers were correct, incorrect, or answered with 'don't know'. I analyzed the effect of internet usage and social media usage while controlling for education, partisanship, gender, living in urban areas, political interest, and traditional media consumption.

My results provide some insight into the issue of internet use and political knowledge. My analyses indicate that there is a positive association between internet use and correct knowledge about politics. I also find that using social media is positively associated with being misinformed, and negatively associated with giving 'don't know' answers. This result might be an indication that social media exposure makes people more confident about what they think they know, subsequently causing people to give incorrect answers instead of saying 'I don't know'.

More qualitative research on the content available on social media and political websites would benefit, and complement, the analysis presented here. Furthermore, experimental research regarding how people consume information online would also provide valuable insight into causal relationships. This research suggests that there might be a simultaneous process in which some internet users get misinformed while others get more informed about politics. This process may also be at play in countries with a similar information environment to Turkey.

## **APPENDIX**

The question used for the measurement of the dependent variable is: "Now, we will ask some questions about the news, politics and elections in our country. We do not expect everyone to know the answers to these questions. Please try to give the best possible answer. If you do not know the answer, do not hesitate to pick the "I am not sure" option. Please choose one of the options for each statement: "Definitely wrong", "Wrong", "I am not sure", "Correct", "Definitely correct"

TABLE A1. MEASUREMENT OF POLITICAL KNOWLEDGE

|   | Definitely<br>wrong | Wrong | I am not<br>sure | Right | Definitely right | No<br>opinion/<br>No answer |
|---|---------------------|-------|------------------|-------|------------------|-----------------------------|
| A parliamentary majority of 2/3 is required to change the constitution  | 1                   | 2     | 3                | 4     | 5                | 99                          |
| According to the Constitution, the President must cut all his/her ties with political parties and therefore cannot pursue a campaign during the election period | 1                   | 2     | 3                | 4     | 5                | 99                          |
| It is constitutionally<br>forbidden for the<br>president to preside over<br>the Council of Ministers  | 1                   | 2     | 3                | 4     | 5                | 99                          |
| The election threshold in Turkey is the highest one in the world.   | 1                   | 2     | 3                | 4     | 5                | 99                          |
| The president can veto laws passed by the GNAT only once  | 1                   | 2     | 3                | 4     | 5                | 99                          |
| Independent runners are not subject to the threshold in the elections.  | 1                   | 2     | 3                | 4     | 5                | 99                          |
| In the majority of<br>democracies, the<br>judiciary is presided by<br>the president or the<br>parliament  | 1                   | 2     | 3                | 4     | 5                | 99                          |
| The majority of world's democracies have parliamentarian system   |                     |       |                  |       |                  |                             |

# Chapter 3—Misinformation, Emotions and Polarization: Observations from Twitter

#### I. Introduction

Social media plays an important role in Turkish political life. Millions of users can now be found on Facebook and Twitter, and these sites have featured prominently during recent major political events. For example, social media sites were used to help organize the 2013 Gezi protests and to muster a resistance to the attempted coup d'état in 2016 (Hutchinson, 2013; El Erian, 2016).

Despite its relative importance, we have limited insight into how people use social networking sites in Turkey. In this chapter, I therefore provide a snapshot of Turkish political Twitter<sup>5</sup> in the lead-up to the 2017 constitutional referendum.<sup>6</sup>

I focus on a number of research questions with the goal of shedding light upon issues that have been widely discussed in the broader literature on social media and politics. First, I work on identifying the types of falsehoods that are disseminated in partisan 'echo-chambers' on social media. Second, I explore whether or not social media is an 'emotional' space where users express their opinions through powerful images, videos and messages. Third, I study how emotions affect the way people deal with political information. Fourth, I seek to understand whether different political

<sup>&</sup>lt;sup>5</sup> I focus on Twitter because it is a platform where political issues are widely discussed. The most important aspect of this chapter is that it provides the groundwork for demonstrating the ways that the social media affects individuals.

<sup>&</sup>lt;sup>6</sup> The referendum was proposed by the governing party, AKP, and MHP, the Nationalist Movement Party. The proposed changes were aimed at changing the parliamentary system to an executive presidential system.

<sup>&</sup>lt;sup>7</sup> Echo-chambers are like-minded enclaves where users limit their information intake to like-minded information/opinions and do not receive challenging information/opinions.

clusters on Twitter have adopted common practices, such as sharing information from individuals with 'fringe' views. Finally, I examine the relationship between traditional and social media, and how they relate to political polarization.

The data used in this chapter were collected using qualitative methods, such as 'participant observation'. This was done by opening two Twitter accounts—one which only followed users who supported the 'yes' side in the 2017 constitutional referendum, and one which only followed users who supported the 'no' side. I read through the feeds on a daily basis during the month leading up to the vote in April 2017 and documented what I found. I continued to observe these accounts until June 2019 and carried out computational analyses of texts, social networks and sentiments.

As most studies on social media are quantitative, I believe that a mixed methods approach provides an alternative perspective that may provide us with new insights. I focus on human users rather than bots and analyze their activities. This approach allows me to delve deeper into a virtual environment where many users discuss political developments.

My findings suggest that the polarized nature of echo-chambers may influence individuals' emotions, which in turn may lead them be less selective about the information to which they expose themselves and others. The more people interact with their echo-chambers about political issues on Twitter, the more confident they become, which may lead to increased polarization. They become angry at the other side and fear the consequences of failure in the election while feeling enthusiastic about the political actor they support. This emotional process facilitates misinformation as individuals become less attentive to whether or not the content that they see is correct, as long as it confirms their political bias.

The remainder of this chapter is structured as follows. I first discuss my methodology, after which I present the observations from the fieldwork supported by computational analyses of tweets and networks. I, then, explain how polarization and emotions are linked to the way people receive information on social media. I conclude by summarizing the findings and discussing the advantages and limitations of this research.

# II. Participant Observation and Lurking

In parallel to the rise of digital technologies, researchers started viewing the online platforms as a space for data collection. Fieldwork carried out in digital media have been labelled with concepts such as digital ethnography, virtual ethnography, and netography. (Boellstorff, 2008; Ardevol, 2012; Postill and Pink, 2012; Hine, 2008 and 2015; Sumiala, Tikka, Huhtamaki, Valaskivi, 2016). Although much of the research on the internet is conducted using quantitative methods, some researchers see the internet as a social and cultural space where qualitative methods should be used (Richman, 2007).

Scholars who study virtual environments have adopted methods of participant observation to analyze virtual spaces (Boellstorff, Nardi, Pearce and Taylor, 2012). Mostly used in studying gaming environments and marginalized groups, participant observation can be a great tool to shed light into communities and cultures in online environments. There can be covert or overt ways to conduct participant observation in the online media (Murthy, 2008). During the fieldwork, the researcher "makes notes, takes screen shots, downloads material, and he or she may also interview informants by meeting them face-to-face or via digital communication media" (Sumiala, Tikka,

Huhtamaki, Valaskivi, 2016: 7).

While there are studies in which researchers participate in Twitter activity (Chretien et al., 2015), my approach is instead based on covert observation due to ethical considerations. These considerations are based on the fact that I am a citizen of Turkey who voted in the referendum and can thus scarcely be seen as an impartial participant. It would therefore not be ethical for me to interact with users in my echochambers. I only observe and lurk (Gehl, 2016; Næss, 2017) on the flow of information on my created timeline and take field notes to detect patterns. As Hine (2015: 57) states "In an online discussion group, for example, it may be quite normal to lurk without posting, and thus to remain invisible to other participants." The only participatory part of this study is that I follow users in order to create the echo-chambers, and am sometimes followed in return (although, of course, I do not post anything).

Thanks to the multifaceted nature of contemporary media, researchers have to process not only words but images, videos, as well as other types of digital information. (Sumiala, Tikka, Huhtamaki, Valaskivi, 2016). I use screenshots of Twitter posts collected from the echo-chambers and notes relating to the same screenshots as the basis of my analysis. As Boellstroff, Nardi, Pearce and Taylor (2012: 114) state, "Screenshots can be an important aspect of data collection." I collected screenshots that showed cases of falsehoods, emotional or polarizing content. For ethical reasons, in this text, I blurred or cropped the screenshots that contain the name and profile picture of the people who had real names and photos on their accounts. I did not do the same for the accounts with generic photos/usernames. In addition to the notes and screenshots from the lurking, I analyze tweets, emojis and retweet networks to support my arguments.

# III. Creating the Partisan Echo-Chambers

Echo-chambers are formed when individuals restrict themselves to the types of information they would like to see (Sunstein, 2001). In such environments, individuals limit their intake of information to sources that confirm their pre-existing political attitudes. Technological structures, such as algorithms, facilitate the creation of echo-chambers by allowing users to defriend and/or mute those who disagree with them or challenge what they believe. In sum, the internet enables individuals to live in political echo-chambers and may also as a consequence polarize them (Sunstein, 2001).

In order to create my echo-chambers, I first created two separate Twitter accounts: *simgearastirma1* and *simgearastirma2*, which includes my first name followed by the Turkish word for 'research1' and 'research2'. The avatars reflect the nature of these accounts as they include both my name and 'arastirma' the word for 'research' in Turkish.

With the first account, simgearastirmal, I first followed the members of the cabinet in Turkey. After this initial step, I wanted to reach and follow less official supporters of the government. One way to do this could be to start following those who follow the cabinet members but given that they have hundreds of thousands of followers this option is neither feasible nor is it effective. Instead, I checked the Turkish 'trending topics' on Twitter and started following individual users, initially around 20 people who used these hashtags and wrote posts in favor of the constitutional referendum. As Bonilla and Rosa (2015: 1) argue:

"Hashtags offer a window to peep through, but it is only by stepping through that window and "following" (in both Twitter and non-Twitter terms) individual users that we can begin to place tweets within a broader context. This kind of analysis requires us to stay with those who tweet and follow them after hashtags have fallen out of "trend." Only then can we better understand what brings them to this virtual place and what they take away from their engagement."

This step allowed me to reach groups of individuals who regularly post in favor of the referendum and strongly support President Recep Tayyip Erdoğan. I increased the number of people I followed by following the accounts retweeted by those I follow. I also followed those who were suggested by Twitter to me. I first checked their position to make sure that I follow those who would actively support the constitutional changes promoted by Erdoğan. My other criteria for following these people was having at least 1000 followers. At the end of my data collection period I was following 203 people. This included some columnists and pundits.

With the second account, I followed a similar path. I first followed the leader of the main opposition party, Kemal Kılıçdaroğlu and his party administration. As a second step, I started checking pro-opposition hashtags. There were fewer pro-opposition hashtags, but I initially followed around 20 people who used the hashtag 'kılıcdaroglunesoyledi' (what did Kılıçdaroğlu say). I followed more people by following those who retweeted those I follow. My criteria for following included tweets written against the constitutional changes and having at least 1000 followers. After this step, I gradually increased the number of people I followed by following news sites that were shared by those I follow. Similar to the other echo-chamber, I followed many users who were suggested to me by Twitter. I also followed some columnists and journalists. I was also in this case following 203 people at the end of my data collection phase.

I followed these accounts between 14 March 2017 and February 2019. I observed the activities of these accounts from approximately 11 am to 6 pm on a daily

basis (with the exception of weekends) during the referendum campaign between 14 March 2017 and 16 April 2017. Afterwards, I collected tweets from several public accounts and hashtags and analyzed the text as well as the networks in which they were shared.

### IV. The Constitutional Referendum in Turkey

A constitutional referendum consisting of 18 proposed changes was held in Turkey on 16 April 2017. The referendum was designed to change the parliamentarian system to an executive presidency with increased powers for President Recep Tayyip Erdoğan. Many critics opposed the changes as they allow the new president (to be elected in 2019) to acquire full control of the government and have the power to redesign the institutions of the country.

Prior to the referendum, Turkey went through a failed coup attempt, as well as many terrorist attacks by ISIS and PKK. Located next to Syria, Turkey is gravely affected by the war. Since the failed coup attempt the country has been under a state of emergency which enabled the governing party to fire or suspend thousands of people who are suspected of being involved or connected to the coup attempt (Kingsley, 2017).

During the referendum campaign AK Party supporters and the MHP leadership were in favor of the proposed changes while CHP, the main opposition party, and the HDP (a pro-minority party) leadership were opposed to the referendum. Many HDP MPs were in jail or were jailed during the campaign. There were various reports of intimidation towards the No campaign (Kingsley, 2017). President Erdoğan and his supporters associated No-supporters with terrorism. Moreover, analyses of the state TV coverage showed that the Yes campaign received far more airtime than the No

campaign (Birgün, 2017). Social media remained an alternative where the opposition found a voice more often than they did in the traditional media.

Another highlight of the campaign was the row between Erdoğan and the Dutch and German governments. Both Germany and the Netherlands blocked Yescampaigners from campaigning in the two countries, and President Erdoğan accused both countries of being fascist. The row led to a diplomatic crisis between Turkey and the Netherlands (Dorroch, 2017). This incident drew lot of attention domestically during which yes-supporters were mobilized against Europe.

Following the referendum, Turkey had one more election in 2018 to elect a new president with the expanded powers granted by the positive result of the referendum. The election campaign was highly polarizing, where Erdoğan and his main contender (Muharrem İnce) campaigned intensely (Lowen, 2018). Turkey also went through a municipal election campaign in early 2019 (HDN, 2019).

Turkey presents a critical case in the study of echo-chambers due to several reasons. First, most studies on the subject are conducted in the West (Barbera et al., 2015), which makes generalizable conclusions difficult. Second, as an increasingly authoritarian regime, Turkey provides a fertile ground for the study of misinformation on social media. Social media sites are the few remaining gateways to accessing alternative news and opinions, given that the majority of Turkish media companies are owned by pro-government businesses (Yılmaz, 2016). Finally, Turkey has had three elections between 2017 and 2019, which makes it an ideal case to observe, as individuals may generate more data on social media during elections and campaigns.

## V. Observations from Two Echo-Chambers

#### A. Shared Practices

As Honeycutt and Herring (2009) emphasize, Twitter can be a place for conversations and collaboration. Users share their daily activities and form a community on Twitter (Java, Song, Tseng, Finn, 2007). A typical day in both of my echo-chambers begins with wishing the Twitter world a 'good morning'. Some twitter users reply to each other and say good morning back. These posts are usually accompanied by pictures of nature or the leaders they support. Some users even celebrate each other's birthday. These interactions symbolize the sense of community in these groups.



Image 1: Two users saying good morning to each other with pictures of Atatürk and flowers

Each echo-chamber has various social media teams that create hashtags and try to make these hashtags appear on the trending topics page, which shows the most popular subjects discussed by Twitter users in Turkey. In each echo-chamber these teams lead the hashtag creation. Some of the people I followed were members of these teams. I observed more teams in the 'yes/pro-AKP' echo-chamber. They also have

other social media groups such as WhatsApp groups or other direct message groups where they discuss the hashtags.

In the pro-AKP echo-chamber there is a daily and coordinated effort to make certain hashtags appear on the trending topics page. There are several accounts that make calls to write about a selected issue at a certain time of the day. Consequently, no matter what time of the day it is there are always pro-AKP or pro-Erdoğan hashtags trending in the Turkey page. Depending on the political agenda, they create more than three hashtags per day that make it to the trending topics in Turkey. I observed more 'no' themed hashtags the closer we got to the day of the referendum.

Some users have two or three accounts in case they get blocked by Twitter. This usually happens when the users from the other side attacks certain accounts by reporting them to Twitter. In such cases the victim informs his or her followers from the spare account and the followers retweet and like their tweets to show solidarity and support.

In the pro-AKP echo-chamber there are at least five types of users:

- 1. *Politicians:* Mostly tweeting about the places they visit and the constitutional referendum.
- 2. Social media leaders: These people have many followers and they ask for support to bring hashtags to the trending topics page. They are very passionate about President Erdoğan and express their support in emotional messages. Some of them have real profile photos whereas many have generic pictures on their profiles.
- 3. *Volunteers:* These are the ones who follow the social media leaders and give support to bring hashtags to the trending topic page. They constantly express their support for President Erdoğan. The topics they cover vary depending on

- the political agenda. They tweet continuously and interact with each other.

  There is a tendency to share conspiracy theories.
- 4. *Information accounts:* These accounts share infographics and visual content about the changes in the proposed system. However, the content they share is usually biased and not completely true.
- 5. Journalists, pundits and fringe news producers: Some pro-government journalists and pundits are very passionate about Twitter and they tweet continuously. There are various news outlets from which users share articles. These are not limited to mainstream newspapers. I have discovered many unknown news sources, which produce junk or misleading news.

Compared to the pro-AKP/'yes' echo-chamber, the 'no'-sides effort to influence the agenda on Twitter seemed less coordinated. I have come across a similar composition of types of users for the 'pro-CHP/no' echo-chamber. The main difference was that there were not as many pundits, social media leaders and none of the 'information' accounts that I observed in the pro-AKP echo-chamber.

#### B. MISCONCEPTIONS ABOUT WESTERN COUNTRIES

As Sunstein (2018: 11) states "Echo-chambers can lead people to believe in falsehoods, and it may be difficult or impossible to correct them." There are several types of misinformation that can be observed in the two echo-chambers that I followed. One type of misinformation is based on conspiracy theories.

As Gorman and Gorman (2017) emphasize, social media has become a platform where conspiracy theories are easily disseminated. In particular in the pro-AKP/'yes' echo-chamber, many users share all sorts of conspiracy theories mostly based on anti-

Europeanism and anti-Christianity. According to many users the West as a whole is against Turkey's development and is supporting those who will vote 'no'. This tendency significantly increased after the diplomatic crisis between Turkey and the Netherlands (Sengupta, 2017). They often talk about a mastermind in the West who is trying to control Turkey's steps towards becoming powerful as it was in the Ottoman period. Many present the referendum as a power struggle with Europe and the West. Some pro-government journalists and pundits support these views with unverified information and comments.



Image 2: The user claims that Germany is expelling Turks



Image 3: The user claims that Europe is trying to do what the failed coup attempt could not

Similarly, in the pro-CHP echo-chamber, many believe that the proposed system is the first step towards a Western intervention in Turkey. Many users claim that this is part of the 'Greater Middle East Project' (Wittes, 2004). Following the referendum, in the event of a 'yes' vote, they claim that Turkey will first be divided into federal states and then split into a Turkish and Kurdish state, which is according to this echo-chamber a step in the Greater Middle East Project.



**Images 4 and 5:** Users claim that the constitutional changes are part of the Greater Middle East

Initiative and will lead to a divided country

#### C. Rumors About the 'Other'

Many cases of misinformation were about spreading rumors about the other camp. For example, Erdoğan supporters have made a default poster frame where they could easily photoshop the photo of a CHP MP and add a false quote under the photo. This type of images is aimed at spreading false information about the opposition party members. For example, in the first picture, it is suggested that the CHP MP had said "I am proud of my Christian identity. I am ashamed to be a Turkish citizen!" which is completely

false. The second one includes a photoshopped image of the main opposition leader saying that he is a fan of Israel.



Images 5 and 6

Another type of information was spreading rumors about CHP's local work. In the image below the user argues that documents prove that CHP bought votes by promising family insurance in the last general elections. There is no such information in the alleged documents.



Image 7

There were also rumors and photoshopped material circulating in the 'no' echochamber. For example, in the first image below it is suggested that a governor is offering anyone who brings a proof that shows they voted in favor of the constitutional referendum 300 TRY in compensation. In the second picture, the user is humiliating a TV anchor for exaggerating the crisis between Turkey and the Netherlands. The picture is photoshopped and shows that the anchor claimed that the police in Netherlands used atomic bombs on Turkish protestors.



Images 8 and 9

Rumors and false news dominated Twitter during the 2019 local election night in Turkey. The main controversy was about the local election results in Istanbul—the largest and most cosmopolitan city in Turkey. The official state news agency stopped updating the elections results around midnight while the opposition candidate claimed that he had won. His victory was confirmed but rumors and false news arguing that the main opposition party (CHP) committed election fraud increased exponentially throughout the following weeks.

The rumors were mostly started and led by AKP officials including the AKP Istanbul chair Ali İhsan Özyavuz. AKP supporters simply built on his arguments. These rumors were strengthened by the commentators on fringe news sites and other partisan pro-government outlets. Some users claimed that this election result was due to an operation by the CIA and other groups such as FETÖ.



Image 10. AKP supporter repeating AKP official's arguments



Image 11. Commentator claiming to explain how a systematic fraud happened

The AKP supporters started two hashtags following the election day: HirsizCHP (CHP the Thief) and HirsizVar (There is a thief) among others to spread rumors about election fraud. These hashtags were not only popular among the progovernment users but also the opposition supporters who wanted to debunk fraud claims. I collected 218,074 tweets through the Twitter Stream API on April 1st and

April 2<sup>nd</sup>. The chart below shows the fast diffusion of retweets on these hashtags over two days (April 1-2, 2019). The total retweet numbers in the course of six hours reached approximately 30,000 on April 1<sup>st</sup> until the live-stream connection was lost at 6 PM.

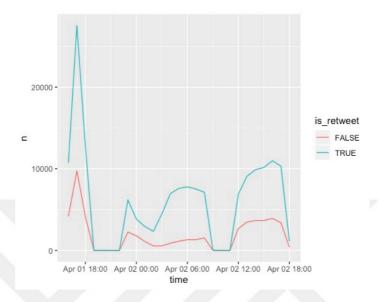


Figure 1. Retweet Count Of Two Rumor Dominated Hashtags

# D. Fringe News Sites

During my research, I have discovered several news sites that provide misleading information in both echo-chambers. For example, during the campaign period developments in Kerkuk (Iraq) were highlighted after the Kurdish administration raised its flag there. Turkey reacted to this by saying that it is unacceptable (Reuters, 2017).<sup>8</sup> In one article by Ak Gazete (that showed up on my timeline) it is claimed that the Kurdish flag has been brought down in Kerkuk. However, there are no photos or any detailed explanations in the article.<sup>9</sup>

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<sup>&</sup>lt;sup>8</sup> Reuters. Turkey's Erdoğan calls on Iraqi Kurds to lower Kurdish flag in Kirkuk. April 4, 2017. https://www.reuters.com/article/us-mideast-crisis-turkey-erdogan/turkeys-erdogan-calls-on-iraqi-kurds-to-lower-kurdish-flag-in-kirkuk-idUSKBN1761PP

<sup>&</sup>lt;sup>9</sup> Ak Gazete. 'Kerkük'te Kürt Bayrağı indirildi'. April 11, 2017. http://www.akgazete.com.tr/dunya/kerkukte-kurt-bayragi-indirildi/33038 The article is removed as of September 8, 2019.

Conspiracy theories or rumors can be supported by adding news articles to the post. News articles add legitimacy to such arguments as news articles supposedly have credibility. For example, AKP pundits/trolls kept arguing that the Gülen organization was planning a spring coup before the referendum. In the post below, one of them, Ömer Turan (Followers: 109,000) shares an article from Süper Haber (Super News) to support his argument. The article suggests that Gülen members share messages that contain the word 'Spring' which is according to them a signal for a new coup attempt.<sup>10</sup>



Image 12

This pundit is popular among some of the pro-government people in my cluster. He increased his follower number by 24,000 in the months following the referendum campaign. I collected posts from his timeline (3200 tweets) in March 2018 using the Twitter API. Below is a 'wordcloud' of his tweets and the rate of sharing for 3 months. His most common words include: FETÖ, scandal, big, fight, terror, alliance, Muslim, Islam, shock, PKK, July (15 July), national.

<sup>&</sup>lt;sup>10</sup> Süper Haber. 'FETÖ'cülerin Gizemli Nisan Mesajları Ortaya Çıktı'. 2017. Retrieved by April 3, 2017. Available online at: <a href="http://www.superhaber.tv/fetoculerin-gizemli-nisan-mesajlari-ortaya-cikti-ozel-haber-48812-haber">http://www.superhaber.tv/fetoculerin-gizemli-nisan-mesajlari-ortaya-cikti-ozel-haber-48812-haber</a>



Figure 2. Word cloud of OmerTuranTV account

This account has been retweeted thousands of times in the period between January-March 2018. His account was suspended in late 2018, although he opened a new one immediately afterwards.

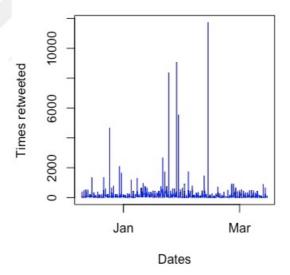


Figure 3. Retweet numbers of the OmerTuranTV account

I also observed that there are Twitter accounts that claimed to be producers of news but mostly share rumors or comments on political events. For example, there is an account named 'Politikaloji' with 25,000 followers. Several users in my 'no' echochamber (including CHP members) followed and interacted with this account. The

account description states that it is about 'Politics and Political News | Reuters' (at the time of the research). The content of the account is mostly opinions in favor of a 'no' vote. There are some tweets that might be considered news, but these have no links that direct the audience to further content. For example, in the first tweet below the account claims that an AKP minister spoke to a small audience and got upset about it because he considered it as a sign that the people are not supporting the constitutional changes. The tweet has no links to an article that builds on the story. It has been retweeted at least 131 times (at the time of the screenshot). In the second tweet the account claims that the polls suggest that the 'Yes' votes are not even 45%. Once again, the tweet is shared more than a 100 times and has no links to an article.



Images 11 and 12

A word cloud of the tweets (n=3200) shared by this account shows some of the most common words by this user. Similar to the pro-government pundit above, this account also tweets about the president, terror, USA, Syria. Unlike the pundit, the account also uses words like resign, punishment, Atatürk (the founder of the Turkish Republic). The tweets of this account have been retweeted thousands of times between May-June 2018.



Figure 4: Word cloud of 'Politikoloji'

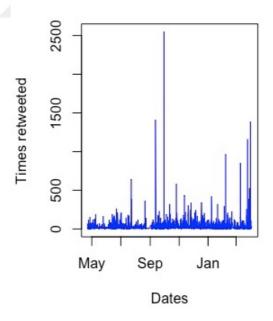


Figure 5: Retweet numbers of Politikoloji

There are other cases of false news. During the campaign period both sides were claiming that the others were siding with terrorists. My 'no' echo-chamber was

spreading false news about how HDP (People's Democratic Party) MP Leyla Zana pledged her support for Erdoğan. There is a news site called 'Sarı Zeybek Haber' which claims that Zana said 'yes' to the presidential system but there is no such pledge in the video that is shared by the news site. The article was shared by 38,000 people on Facebook and viewed more than 300,000 times according to the numbers on their web site. The web site contains other similar false news stories.



Image 13: "Leyla Zana's caught red-handed"

## E. Polarization

The more people I followed, the more I observed the degree of polarization in these echo-chambers. In both echo chambers, many users had descriptions of themselves and their account. In the 'yes' camp, users wrote down their support for President Erdoğan, while in the 'no' camp users expressed support for Mustafa Kemal Atatürk, the founder of the Turkish Republic. This division symbolizes the cleavages that exist in the society

<sup>&</sup>lt;sup>11</sup> Sarı Zeybek Haber. 2017. 'Hadi Buyur! Leyla Zana'nın Kasedi Piyasaya Düştü'. Retrieved by March 15, 2017. Available online at: <a href="https://sarizeybekhaber.com.tr/sok-pkk-li-leyla-zana-dan-erdogan-a-jet-yanit-biz-evet-diyoruz">https://sarizeybekhaber.com.tr/sok-pkk-li-leyla-zana-dan-erdogan-a-jet-yanit-biz-evet-diyoruz</a>

as secular individuals support Atatürk while conservative individuals support the current president Recep Tayyip Erdoğan.



Image 13: User expresses support for Atatürk

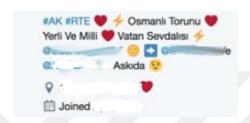


Image 14: User defines herself as a 'grandchild of the Ottomans'

Moreover, in the 'no' echo-chamber, some users warned the supporters of AKP to not follow them or face being blocked, which is an indicator of polarization since these people do not want to interact with anyone who supports the government party.

For example, a simple network analysis of Twitter users who add the hashtags #erdoğan or #rte supports this observation. The graph below is a visualization of 1812 tweets live streamed for an hour on 11 February 2019. The light green cluster on the left is predominantly composed of pro-government Twitter users. The members of this cluster use other hashtags such as #sizsaldırdıkçabizdevamedeceğiz (the more you attack the harder we continue). The darker green cluster is composed of people who demand a law about early retirement.

The graph is originally an interactive graph and can be fully viewed here: http://rpubs.com/simgeandi/466461.

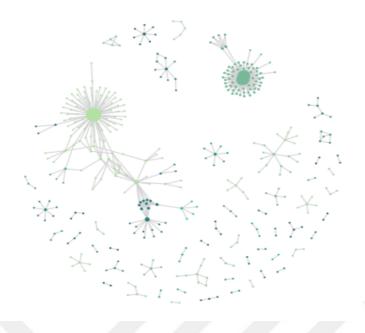


Figure 6: Network analysis of #rte and #erdogan hashtags

Retweet or mention networks support this observation. The retweet network of some of the hashtags used during the period I followed these accounts reveal some supporting evidence with regards to how these accounts share propaganda among themselves. For instance, #cehapekazanamazçünkü has been a popular hashtag among the pro-government cluster members. The hashtag means that CHP—the main opposition party—cannot win and many members of my pro-government cluster share this hashtag to share jokes, false accusations as well as opinions. I collected 5,000 tweets from this hashtag on 12 February 2019 and selected the top 500 tweets to visualize the network. The retweet network is quite compact, with two large clusters and several small ones all connected to each other. The node sizes show the in-degree centrality of the users in the network. The larger nodes indicate the popularity of that user within the network.

<sup>&</sup>lt;sup>13</sup> A more interactive version of this network can be viewed on this link: http://rpubs.com/simgeandi/466009

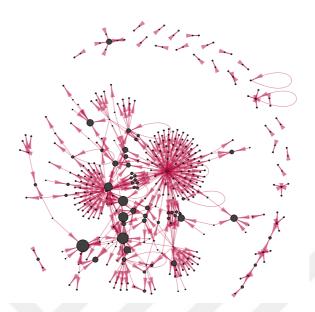


Figure 7: Retweet network of #cehapekazanamazcunku

I also checked if people who use this hashtag include other pro-government hashtags in their tweets. Below are visualizations of the hashtags and their user network. Light blue dots represent the hashtags and the dark blue dots are the users who tweet using at least one hashtag. The size of the light blue dots indicates the popularity of the hashtag. The most popular hashtags that are connected to #cehapekazanamazçünkü are #hainebozkurtmazlumarabia (wolf to the traitor, 'rabia' to the underdog—symbolizes the coalition between the government and the nationalist party) and #millibekaiçin (for the national survival—another pro-AKP hashtag). There are other less popular hashtags like #chppişmanlıktır (CHP means regret).<sup>14</sup>

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<sup>&</sup>lt;sup>14</sup> The original version of this graph is interactive and can best be viewed on this link: <a href="http://rpubs.com/simgeandi/466475">http://rpubs.com/simgeandi/466475</a>

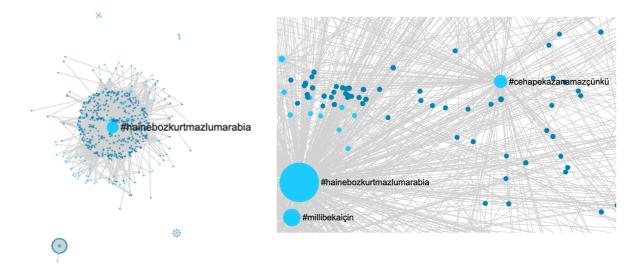


Figure 8 and 9: Network of pro-government hashtags

## F. Alternate Realities

The level of polarization in these communities was sometimes reflected in the way they interpreted political developments. It was almost as if there were two competing realities. Each side has media outlets that confirm their existing political stance. This availability helps them justify whatever is happening from their own perspective and delegitimize the arguments made by the opposing side.

An important characteristic of social media is the ease of commenting about political issues by using a strong language which is usually absent in traditional mainstream media. For example, there was an incident that received some attention from both traditional and social media on March 21st. Ali Gül, a young man who filmed a video in favor of a 'no' vote was arrested. The 'no' echo-chamber and the 'yes' echo-chamber disagreed on why he was arrested. To have a better understanding of the issue, I present the differences in the way this incident was reflected on the traditional newspapers' and social media.

The issue did not get much attention in printed newspapers. For example, Hürriyet, the newspaper with the greatest circulation, did not even cover this issue on its website. Another mainstream newspaper Habertürk (21 March 2017) covered this issue by using objective language on its website. The article stated that Mr Gül was arrested because he was accused of supporting the coup attempt and insulting Islam.

The language gets harsher the more polarized the newspaper is. For example, Cumhuriyet (21 March 2017), an opposition newspaper, published an article on its website emphasizing the reactions of the main opposition party. Another newspaper, Takvim, also known for its support for the government and fabricated news, published an article (21 March 2017) with misleading content both on its website and social media accounts. One article headline was 'No propaganda by German foundation'. The article claims that German foundations, which are supposedly involved in divisive and destructive activities against Turkey, are now organizing 'no' vote propaganda aimed at manipulating the will of the Turkish people. The article continues with several accusations against German foundations in Turkey and claims that Ali Gül insulted Islam, Erdoğan and all our national values, and that he was arrested on those grounds. On their Twitter account, they published content that said "Germans within us!"



**Image 15:** This newspaper's Twitter account shared a post that said 'No propaganda sponsored by German Foundation. Germans within us!'

When I started analyzing this social media scene, I observed that the members of the two echo-chambers I followed were more passionate about this issue than the mainstream media. The two echo-chambers I created for this research disagreed about the incident in every possible way. Pro-AKP echo-chamber members shared articles from pro-government sources to prove that he was arrested for insulting Erdoğan and religious values, while the pro-CHP echo-chamber members shared posts about him being arrested for the No video he made. In the pro-AKP echo-chamber there was an account named FETÖ Gerçekleri (FETÖ Facts) that shared many posts about this incident. The people I follow in the pro-AKP echo-chamber accused the man of being a "traitor", while the pro-CHP echo chamber claimed he was innocent and a victim of the oppressive regime. In both echo chambers people used strong language to support their views. In image 16 below, the users are arguing that Ali Gül is a 'traitor' while in image 17 the user is arguing that the arrest was due to the video and that Turkish democracy is in 'ruins'.



Images 16 and 17: Pro-AKP echo-chamber and a Pro-CHP echo-chamber

As this incident shows even fringe issues, more or less ignored by the mainstream media, can make it to the agenda on social media. Social media users

articulate their opinions by using powerful words to influence other users' opinions. Imagine a person who does not have a social media account. He reads Hürriyet and is not even aware of this incident, while a Twitter user who checks his timeline hourly, is very much aware and is already opinionated about the issue.

This is the process by which the emotions of voters are affected. The more they get exposed to their echo-chamber, the more opinionated and emotional they become.

This may, in turn, trigger more information sharing from sources that they trust.

#### G. Interpretation Replaces Information

Another instance of polarization can be observed in the way people interpret information. For example, there were some Twitter accounts that supposedly spread objective information in the 'Yes' echo-chamber. These accounts share infographics and posters that supposedly explain the constitutional changes. There is an effort to inform people, but the information provided is biased. For example, @CBSisteminedir (Whatisthenewpresidentialsystem, followers: 47,000, date: 14.03.2017). As the name suggests this account claims to be providing information on the proposed presidential system. There are comparisons between the old system and proposed changes. However, the information presented usually only consists of half-truths. While presenting the information on the proposed system, this account does not provide the full picture and makes far-reaching assumptions about what good the system would bring to the people.

For example, in one of the posts, the account suggests that the new system will ensure full independence and will prevent all external threats. We do not see anything that explains why this would happen. The audience is just told that this would happen because the proposed system is good. In the name of informing its Twitter audience, accounts like this one provide half-truths about the proposed system. Interpretation

replaces objective information and the account creates an alternative reality where the system fixes many potential problems in Turkey's future.

When we examine another similar account @YeniCBSistemi <sup>15</sup> (23,300 followers, Date: 13.03.2017) we see a similar effort. In a post by this account, it is argued that the judiciary cannot be fully free of influence. Therefore, the important thing is to ensure the judiciary is not influenced by 'inappropriate' interference. What is meant by this inappropriateness is not explained in the post, nor is the anti-democratic implication that it is natural for a democracy to have a judiciary that is always under external influence.

The problematic part is that these account names and the account descriptions imply that they provide objective information. However, the provided information is limited while there is a lot of projection and far-reaching interpretation of the potential consequences of the proposed system. Moreover, users share these posts thinking that they are spreading objective information. For example, this is one of the reasons why the 'Yes' camp was having a very difficult time in understanding why the 'No' camp was rejecting the proposed presidential system. For them, there was proof that the proposed system was good. Both sides receive biased information, and, many users are therefore unable to recognize that there is another side to the story. Moreover, the one-sidedness of echo-chambers strengthens this tendency.

#### H. EMOTIONAL USERS

The users in both camps tried to appeal to the emotional side of other users during the referendum campaign.

<sup>&</sup>lt;sup>15</sup> Both of these accounts were deactivated after the referendum. Screenshots from the accounts are available upon request.

Both echo-chambers had various social media teams that worked on hashtags and tried to make them popular on the trending topics page. In the pro-yes echo chamber, this effort is mostly combined with expressions of love and support for President Erdoğan. He is presented as almost a godly figure who can bring peace and stability to the country. Almost all the volunteers and social media leaders have shared charismatic photos of Erdoğan, usually combined with quotes by him. Many users share videos of his speeches or make their own videos of him with emotionally evocative music in the background. President Erdoğan is presented as a leader who can challenge the West and thus poses a threat to the West.



Image 18

This image of President Erdoğan is supported by posts about the West cooperating with the 'no' camp in the campaign process. Many users claim that Europe is cooperating with the 'no' camp because they do not want a strong and independent Turkey. They present President Erdoğan as a warrior who fights against foreign and domestic powers to save his country. The purpose of these posts is likely to create enthusiasm about President Erdoğan's rule.

The imagery with the sun is used in the main campaign material of CHP (Image 19). This post associates CHP's campaign with Merkel, Wilders, Gülen and the leader of the PKK, and implies that the No campaign is cooperating with foreign powers and

terrorist organizations. This image can also be seen as an attempt to induce fear among Erdoğan supporters since it implies that foreign powers will determine their future if the No vote wins.



Image 19

Another observation that I made was the prevalence nostalgia in both echochambers. In the 'no' echo-chamber, there was a tendency to express love and obedience to Atatürk and envy of the early Republican era. As those in the 'yes' camp shared charismatic Erdoğan photos, users in the 'no' camp shared charismatic photos of Atatürk. In the post below, the user is sharing posts that pledge their obedience and support for Atatürk's principles.



Image 20

As expected, the pro-AKP echo-chamber pursued a different nostalgia. They envied the Ottoman era and presented the referendum as an opportunity for an awakening from the Republican era which was, according to them, dominated by Western influence. I regularly come across posts about how Turkey was a continuation of a great empire, governed by great sultans. These posts were, again, aimed at creating enthusiasm about Erdoğan's rule and power. The new system was to be applauded by these users as it would enable Turkey to return to its powerful past.



Image 21



Image 22

Overall, both echo-chambers facilitated the dissemination of emotional content like videos or posts with powerful comments and images in favor of or, in opposition to, President Erdoğan. In the pro-AKP echo-chamber this activity was aimed at creating enthusiasm among the supporters of Erdoğan and fear among those who oppose him. In the No echo-chamber, users shared images of Atatürk to balance President Erdoğan's image on social media. In both echo-chambers users also tried to induce fear among themselves by suggesting that Turkey would be divided should the other side win. In moments of crisis, when these clusters became even more polarized, such as the diplomatic crisis with the Netherlands, users were more active and careless in terms of the information they shared. They disseminated more conspiracy theories and emotional content (for example, nostalgic content about the powerful days of the Ottoman Empire) to support Turkey's stance.

A good addition to this analysis would be a sentiment analysis of these accounts' tweets. There is, however, no Turkish dictionary available for sentiment analysis at the time of this research. Instead, I analyzed the emojis used in these echochambers as many social media users add emojis<sup>16</sup> to their tweets to express their emotions.

I initially checked if people who used the hashtag #CeHaPeKazanamazÇünkü added any emojis to their tweets. For this, I analyzed the 5,000 tweets I collected from this hashtag. Below is a table that shows the 10 most common emojis and the times they were used in this hashtag. In only 5000 tweets, there are at least 2499 emojis.

<sup>&</sup>lt;sup>16</sup> Emojis are small digital images that users utilize to express their feelings or thoughts.

TABLE 1. TOP 10 EMOJIS USED IN THE #CEHAPEKAZANAMAZÇÜNKÜ

| 1.  | Face with tears of joy                     | 1476 |
|-----|--|------|
| 2.  | Rolling on the floor laughing              | 324  |
| 3.  | Winking face                               | 191  |
| 4.  | Turkey                                     | 186  |
| 5.  | Heavy check mark                           | 134  |
| 6.  | Backhand index pointing right              | 58   |
| 7.  | Grinning face with smiling eyes            | 41   |
| 8.  | Exclamation mark                           | 35   |
| 9.  | Smiling face with open mouth & closed eyes | 27   |
| 10. | Smiling face with sunglasses               | 27   |

During the participant observation period, I observed how pro-government Twitter users tried to create enthusiasm among their supporters. One way of doing this is by ridiculing the opposition. The hashtag #CeHaPeKazanamazÇünkü is a perfect example of these attempts. Most pro-government users who contributed to this hashtag attempted to make mockery of the main opposition party. As this list shows, most emojis used in this hashtag are smileys that are laughing or grinning. The graph below presents the sentiment score over time, with higher scores indicating more positive sentiment (Peterka-Bonnetta, 2017).

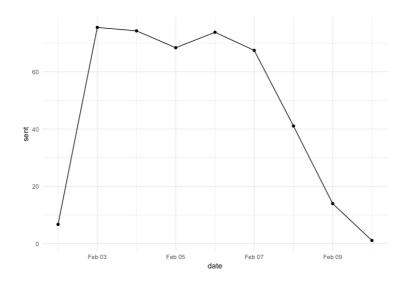


Figure 10: Sentiment scores of emojis in #CeHaPeKazanamazCunku

There are differences between hashtags in terms of sentimentality. Another popular hashtag among pro-government users on Twitter prior to the local elections in 2019 was #hainebozkurtmazlumarabia (wolf to the traitor, 'rabia' to the underdog—symbolizing the coalition between the government and the nationalist party MHP). Once again, I collected 5,000 tweets from this hashtag. This hashtag had fewer emojis than the previous hashtag. Given the nationalist symbolism of the hashtag, the most used emoji is the Turkey flag.

Table 2. EMOJIS USED IN #HAINEBOZKURTMAZLUMARABIA

| 1.  | Turkey                                      | 359 |
|-----|---|-----|
| 2.  | Rose  | 133 |
| 3.  | Face with tears of joy                      | 120 |
| 4.  | Tulip                                       | 119 |
| 5.  | Smiling face with open mouth & smiling eyes | 75  |
| 6.  | Seedling                                    | 65  |
| 7.  | Thinking face                               | 60  |
| 8.  | Heavy check mark                            | 48  |
| 9.  | Backhand index pointing down                | 44  |
| 10. | Grinning face                               | 15  |

The sentiment score over time is quite different to the previous hashtag. This hashtag seems to be less positive than the previous one, as indicated by the lower sentiment score. <sup>17</sup>

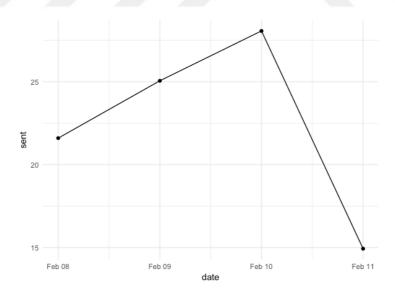


Figure 11. Sentiment score of #hainebozkurtmazlumarabia

66

<sup>&</sup>lt;sup>17</sup> The main R packages used for the analyses here are: rtweet, sigmjs, twitteR, ggplot, wordcloud. Please see the references for further information.

Overall, both echo-chambers I followed shared emotional and opinionated content. The members of both echo-chambers became less selective about the quality of the information they shared during important political events. They shared false news, rumors and conspiracy theories. The more they were exposed to their like-minded environments where they found support and justification for their political beliefs, the more convinced they were about how the other side was wrong.

#### VI. Conclusion

In this chapter, I observed two echo-chambers on Twitter during a period of political campaigning. My preliminary research took a month, and involved participant observation to collect data. I created two echo-chambers that supported the two sides of the constitutional referendum in Turkey. I subsequently carried out text, sentiment and network analyses using Twitter data. My observations revealed that social media facilitates polarization and makes users more emotional, which may be connected to misinformation.

I observed several trends in my echo-chambers. First of all, mis- and disinformation comes in various types. Users often spread rumors about the opposite camp and support these rumors with articles from partisan websites that are typically misleading. Many users share conspiracy theories claiming that foreign powers are trying to interfere with Turkey's domestic affairs. On each side, the users claimed that the other side is ignorant and is unaware of their voting preferences. Moreover, there were accounts which claimed to be providing objective information while spreading misleading information and biased interpretation of the constitutional changes. Further, most users in the study seem unaware of (or uninterested in) the quality of information

that they consume and share. In sum, Twitter is used as a tool for disinformation campaigns in these echo-chambers.

Secondly, it is very easy for a politically biased individual to access polarizing content on Twitter. When I first started creating the echo-chambers all I had to do was to find a hashtag that supported the view of my echo-chamber (yes or no). After that Twitter's suggestions for people to follow were very suitable for the views of the echo-chambers that I joined. Social network analyses of tweets posted by the members of these echo-chambers support the idea that they are linked to each other. Also, these users retweet each other and the hashtags that they use are often connected.

Once I created the two echo-chambers, I observed that they both had their own information sources that provide hyper partisan content. As can be seen in several user profiles presented above, some users do not even want to be followed by those from the opposite side. When two sides discuss the same issue, it looks like they are in parallel worlds living in totally different realities.

Emotional messages are frequently shared in both echo-chambers. There seems to be a relationship between polarization and the density of emotional messages shared. In the 'yes' camp, these messages are about love for Erdoğan while in the 'no' camp they express love for Atatürk. In the 'yes' echo-chamber many users were enthusiastic about the days of the Ottoman Empire and feared the consequences of a No vote. As Sunstein (2018: 16) state "If your Twitter feed is full of pessimistic people, verging on despair about the economy or the fate of your nation, you'll become pessimistic as well." A likely consequence of echo-chambers on social media is "fragmented feelings with respect to specific objects and positions" (*ibid*). As the sentiment analysis of the emojis used in some of the pro-AKP hashtags supports my argument that these echo-

chambers share emotional content according to the nature of their goals with the hashtag.

The more polarized the echo-chambers become, the more emotional material they seem to share. The more emotional users become, the less they pay attention to the quality of information that they receive and consequently share. This is even more apparent during important events such as elections. When polarization over a political issue takes place, individuals get emotional about the issue. They reflect their past experiences and future expectations about political developments upon that incident and feel afraid or enthusiastic about it. In the 'No' echo-chamber, any political incident can become a symbol of how bad the AK Party government is, which also indicates that the future is dark. Whereas in the 'Yes' echo-chamber, majority of political issues and the way the government deals with them creates enthusiasm about today and the future. These feelings are mostly fueled by the social media leaders who continuously share content. The more emotional these users get about a political issue, the more they post about it. The more they post, the less selective they are about the source and the content. The activities in these echo-chambers indicate that there may be a mechanism between polarization, emotions and misinformation.

The research carried out in this chapter is descriptive, and despite its many advantages, has some limitations. For one, it produces potentially unrepresentative results as the characteristics of echo-chambers may vary by user. Echo-chamber environments can be totally different for non-partisan users.

This research could be strengthened by interviews with the individuals I followed. However, probably due to factors such as the political climate in Turkey, none of the people that I contacted agreed to be interviewed.

All things considered, I believe this chapter provides a unique approach to studying a partisan social media environment by using mixed methodology. Particularly by providing an in-depth analysis of a much-debated phenomenon—echochambers—this chapter advances our understanding of mis- and disinformation on social media.

# **Chapter 4 – Anger and Echo-Chambers: The Sharing of False Information**

## I. Introduction

Social media is becoming an increasingly important source of political information (Newman et al., 2018). It has, for instance, become the primary source of news for over 40 percent of adults in countries like the UK, US, and Turkey (Newman, 2017). Social media is, however, simultaneously the main conduit for false news (Bessi et al., 2016). Indeed, few social media users think that social media sites facilitate separating facts from falsehoods (Newman, 2017) and many academics, politicians and journalists argue that false news on social media played a significant role in the 2016 US Presidential election (Allcott and Gentzkow, 2017).

While we do not fully understand the forces underlying the spread of false news on social media, emotions are likely to play a role (Bakir and McStay, 2018). Anger might, for example, mobilize people and make them more likely to share content, while also increasing the probability that they overlook factual inaccuracies and faulty inferences (Valentino et al., 2011; Lerner, Goldberg, and Tetlock, 1998; Tiedens and Linton, 2001).

Another potentially important factor is the type of social media network to which individuals expose themselves. Many users find themselves in like-minded social media environments—also known as echo-chambers—where the veracity of content may be overlooked, as long as it confirms with the groups pre-existing political

beliefs (Sunstein, 2001 & 2018; Törnberg, 2018; Zollo and Quattrociocchi, 2018; Guess et al., 2018).

There may also be an interactive effect between anger and participating in echochambers. This may be due to trust that users feel when they are among network members who have similar political attitudes. It may also be the effect of having an audience. When users are in echo-chambers, and receive political information that makes them angry, they may be more inclined to share for appreciation or support from their network. This process may facilitate the sharing of false or misleading information, as users are likely to overlook inconsistencies or unprofessionalism to gain praise or attention from their network.

While several studies find an association between anger, social media environment and the sharing of information online, we lack evidence that establishes a causal link between these factors (Berger and Milkman, 2012; Stieglitz and Dan Xuan, 2013; Törnberg, 2018; Zollo and Quattrociocchi, 2018; Guess et al., 2018). This paper addresses this gap by presenting two lab experiments that examine how anger and likeminded online environments affect the sharing of false news.

The first experiment is conducted in Turkey and looks at how anger and being placed in a (hypothetical) like-minded social media group influences people's willingness to share a false news article about Syrian refugees. The second experiment is carried out in the UK and examines how anger and being told that you are in a like-minded/cross-cutting chat group affects what people say about a misleading news article on immigration.

The experiments provide us with a number of noteworthy results. Being told that you are in a (hypothetical) likeminded partisan cluster increases the willingness to share a false news article. However, being informed about the attitudes of the other

participant in a chat group decreases the sharing of false information. Finally, there is no statistically significant interactive effect between anger and echo-chambers on people's propensity to share of false information in these experiments.

The rest of the paper is structured as follows: Section II presents the theoretical background and previous literature, and Section III and IV include detailed explanations of the two experiments. Section V discusses the results and limitations and concludes the paper.

## II. Theoretical Background

#### A. The Prevalence and Effects of False News

False news can be defined as news articles that are "intentionally and verifiably" incorrect and that are aimed to "mislead readers" (Allcott and Gentzkow, 2017: 213). These types of articles have been used for a variety of purposes, ranging from the disruption of elections to the incitement of violence (The Guardian, 2016). Moreover, large swathes of false news are designed to feed into the partisan sensitivities of voters and to create confusion about political matters. Many false news articles also contain some emotional appeal (Owen, 2017) and are intended to provoke outrage (Bakir and McStay, 2018).

There are several factors that are likely to influence whether people believe in, and share, false news. For example, delusional people (Bronstein et al., 2019) and people who lack analytical thinking skills (Pennycook and Rand, 2018) are more inclined to believe false news headlines. Further, some people share news articles to influence their network (Oeldorf-Hirch and Sundar, 2015) or to frustrate other users (Chadwick, Vaccari and O'Loughlin, 2018). People with lower digital media literacy –

such as older people – are more likely to share false news on social media (Guess et al., 2019). Another study shows that conservative voters are more likely to encounter and share false news on Twitter (Grinberg et al., 2019).

Social media enables users to disseminate information to thousands—or even millions—of people without any editorial gatekeeping or other mechanisms that check the veracity of claims (Zollo et al., 2015; Allcott and Gentzkow, 2017). Social media has also drastically reduced the costs of disseminating false news (Carson, 2017). This reduction has resulted in a deluge of unsubstantiated rumors, false news, and hoaxes on websites like Twitter and Facebook (Bessi et al., 2016). For instance, Facebook users spread 115 false pro-Trump stories for more than 30 million times, and 41 false pro-Clinton stories a total of 7.6 million times ahead of the 2016 presidential election (Allcott and Gentzkow, 2017).

The most popular false news stories on Facebook were disseminated more than the most popular mainstream news articles (Silverman 2016)—and perhaps most importantly, among those that read false news stories many reported that they believe the veracity of the articles (Silverman and Singer-Vine 2016). Furthermore, false rumors are not easy to eliminate as they reappear over time and mature into more exaggerated forms (Shin et al., 2018). This has led several academics, politicians, and observers to claim that false news constitutes one of the most significant threats to democracies (Allcott and Gentzkow, 2017; Lazer et al., 2018).

However, we have yet to causally establish what motivates individuals to share false news—as well as information more broadly—in their social networks.

## B. Anger and Sharing Behaviour

Hasell and Weeks (2016: 645) define anger as "an approach emotion that occurs when an injustice is perceived to have occurred and is associated with mobilization, taking

action, and behaviors that seek restitution or punish others" (see also Carver & Harmon-Jones, 2009; Frijda, 1986; Lazarus, 1991; Nabi, 2003). Arpan and Nabi (2011) state that anger can be evoked mainly through being exposed to information that challenges your point of view or when you receive any offensive information.

Anger is thought to mobilize individuals when they need to defend themselves or correct a mistake. When an individual feels angry "his or her attention is focused, and there is a desire to strike out at, attack, or in some way get back at the source of anger or that which is blamed for goal obstruction." (Nabi, 1999: 298). Therefore, anger can both be "an energizer and organizer of behavior" (Nabi, 1999: 298).

According to Arpan and Nabi (2011), anger can lead to an increase in the desire for additional information that conforms with pre-existing beliefs. For example, when an individual receives information that is against his or her preferred party, he/she might seek more information to correct the challenging information.

Valentino et al. (2008) show that anger increases political interest. Valentino et al. (2011) support this claim by documenting how anger increases individuals' motivation to participate in politics. Furthermore, Weeks (2015) shows that angry people are more likely to perceive misleading information due to partisanship, and end up with conclusions that support their prior beliefs.

Hasell and Weeks (2016) posit that one way for individuals to participate in politics is by sharing political information online. People might want to share positive information about their preferred party or negative information about the opposition to punish the supporters of the other political parties. Even though several emotions can result in miscalculations, anger may particularly be significant since anger is more likely to increase overconfidence in people's beliefs.

Previous literature provides some support for this argument. For example, anger suppresses the willingness to seek information about political candidates running in elections by reducing the time spent to look for additional information (Valentino et al., 2008). Smith and Ellsworth (1985) argue that anger is linked to a feeling of certainty and confidence about situations. Moreover, anger increases reliance on heuristics. Angry people have been shown to make shortsighted and stereotypical conclusions (Lerner, Goldberg, and Tetlock, 1998; Tiedens and Linton, 2001). Weeks (2015: 703) argues that "anger may enhance the motivated reasoning process." These features of anger may lead individuals to have less desire to gather additional information about political events or candidates once they receive information that fits their bias. The angrier individuals get, the less systematic they might be in their evaluations of political issues (Tiedens and Lerner, 2001). As Suhay and Erişen (2018) show, anger may increase adverse reactions to incongruent arguments.

Berger demonstrates that there is a difference between high and low arousal emotions in terms of information sharing. High arousal emotions, such as amusement and anxiety, lead to more social transmission of information in comparison to low arousal emotions such as contentment and sadness (Berger, 2011). Stiglitz and Dan Xuan (2013) show that emotional content disseminates more in quantity and easier than neutral content on social media sites like Twitter. As Hasell and Weeks (2016) demonstrate, anger— induced by consuming partisan news— can be associated with increased information sharing about election campaigns. The authors also show that the partisan nature of media can trigger anger in individuals, which in turn may lead to an increase in information sharing.

Based on theories of emotion, it is likely that individuals that partake in partisan social media environments (or echo-chambers) experience higher levels of anger.

Angry individuals may get attracted to hyper-partisan news that confirms their views and disregard the counter attitudinal information (Song, 2018). Furthermore, angry individuals may be more reliant on partisan cues and may disregard the possibility that what they are reading is incorrect.

## C. The Effects of Echo-Chambers

Echo-chambers are clusters on social media where individuals primarily receive likeminded information and follow others who share similar opinions while discarding opposing or challenging information and views (Sunstein, 2001 & 2018). Empirical studies have provided insight into the degree that echo-chambers exist on popular social media sites. Gaines and Mondak (2009) show that ideologically similar students are inclined to form clusters on online social networks between. Another study finds that people who have congruent political views are more likely to be linked on Facebook (Gilbert and Karahalios, 2009).<sup>18</sup>

Other research supports these findings by demonstrating the existence of highly segregated political clusters on Twitter (Conover et al., 2011; Rainie and Smith, 2012). Analyzing Facebook data from Italy and the US, Zollo and Quattrociocchi (2018) show that as users join echo-chambers, they get exposed to likeminded and inaccurate information. Törnberg (2018) finds that echo chambers can facilitate the dissemination of misinformation, particularly when a piece of information or opinion aligns with the attitudes of the echo-chamber. Guess et al. (2018) find that Facebook serves as the most effective site for the spread of false news by facilitating the reach of false articles to partisan groups.

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<sup>&</sup>lt;sup>18</sup> There is also a burgeoning literature on echo-chambers suggesting that they are not as prevalent as once thought. See for example: Barbera et al. (2015), Garrett (2017).

Social media sites facilitate the dissemination of polarizing, emotional and incorrect information (Howard et al., 2017). False news, rumors, conspiracy theories, as well as hoaxes disseminate quickly via echo-chambers (Bessi et al., 2016). The algorithmic structure of social media sites incentivizes producers to oversimplify content, as this generates more likes. This structure might lead to the production of content that is polarizing and emotional (Del Vicario et al., 2016a).

Moreover, Zollo et al. (2015) find that polarized users are also negative when they communicate with each other. The more active a user gets, the more negative her comments get. Moreover, homophilous clusters on social media host angry comments about real-world events by users (Fan et al., 2014).

Echo-chambers might be influential in provoking anger among individuals because of continuous exposure to like-minded information. As Bessi et al. (2016), demonstrate, there may be a correlation between the level of user engagement on good or malicious content and the number of friends who have similar patterns of information consumption. As individuals receive like-minded information about political matters, they may become more convinced of their stance on the issue. They may also get angry at the opposition or the government whom they hold responsible for the political problems about which they read.

Echo-chambers are also environments where individuals have an audience to impress. Sharing news in an emotional manner can be a good way to get attention from the members of an echo-chamber. The more engaged a person gets in an echo-chamber, the more likely that he or she will become angry at the opposition and share articles to punish or raise awareness about the other side. Moreover, in echo-chambers, users share information that caters to the interests of the members of their echo-chamber. Therefore, sharing behavior, when angry, might be more common among like-minded

people since individuals like getting support and recognition for their posts. Knowing that they would draw the attention and get the support of their echo-chamber, angry individuals might be more inclined to ignore inaccuracies and share false information in like-minded environments.

## III. Research Questions and Hypotheses

The study primarily strives to answer the following research questions:

- **RQ1.** Does anger affect the sharing of false news on social media?
- **RQ2.** Does anger affect how people interpret false news that they read on social media?
- **RQ3.** Do social media echo-chambers affect the sharing of false news?
- **RQ4.** Do social media echo-chambers affect how anger influences sharing behavior?

The research questions will be operationalized through the following testable hypotheses:

H<sub>1</sub>: Anger increases the probability that participants share false information that is aligned with their prior beliefs

H<sub>2</sub>: Anger increases the probability that participants believe that the news article they read is correct

H<sub>3</sub>: Individuals are more likely to share false information in an echo-chamber compared to non-echo chamber

H<sub>4</sub>: Echo-chambers increase the probability that participants believe that the news article they read is correct

H<sub>5</sub>: Anger has a larger effect on the probability of sharing false information

when participants are presented with an echo-chamber as opposed to a non-echo

chamber audience

IV. The Pilot Experiment

A. Research Design

The experiment was conducted in the Social Impact and Media Lab at Koç University

in Turkey. Participants were recruited from the subject pool of Department of

Psychology and International Relations. They were asked to take part in a study on

social media usage. The subjects received bonus credits from a psychology course or

in International Relations courses.

Participants were initially asked to complete a pre-test questionnaire to measure

their level of partisanship, attitudes, opinions, and knowledge on particular policy

issues as well as various socio-economic characteristics. The questionnaire and the

remainder of the survey were completed using the survey platform Qualtrics. Koç

University Committee on Human Research gave ethical approval for this research.<sup>19</sup>

Participants were then randomized into one of six groups:

1. Anger treatment with echo chamber sharing audience

2. No anger treatment with echo chamber sharing audience

3. Anger treatment with non-echo chamber sharing audience

4. No anger treatment with non-echo chamber sharing audience

5. Anger treatment with control audience

6. No anger treatment with control audience

<sup>19</sup> IRB Number: 2018.061.IRB3.040

1.0

**TABLE 1. TREATMENT GROUPS** 

| Treatments                 | Anger   | No anger |
|----------------------------|---------|----------|
| Echo chamber audience      | Group 1 | Group 2  |
| Non- echo chamber audience | Group 3 | Group 4  |
| Control (audience)         | Group 5 | Group 6  |

Participants in the 'anger groups' were asked to write about a political issue that had made them angry in the past. Among the students who were assigned to the anger treatment, only one student refrained from writing a proper answer. In the sample, 71 people were assigned to the anger treatment, and 73 were assigned to the control group.

After receiving the anger treatment (or control message), all study participants were shown a false news article about immigration. The participants read the article online by clicking on a link that appeared on the screen with the headline of the article on top and were asked to click on the link and read the article. The article was framed from an anti-government perspective. The article claimed that an MP of the main opposition party in Turkey (CHP) made a statement against government spending on Syrian refugees in Turkey. Both the MP's name and the numbers included were fake.

# CHP Milletvekili: Türkiye'den Suriyeli Mültecilere Dev Kaynak

🛔 aksamhaberleri.press 🕒 Uncategorized 🕓 May 11, 2018 🗏 0 Minutes



CHP Milletvekili İhsan Kaynaroğlu

CHP milletvekili İhsan Kaynaroğlu hükümetin Suriyeli mültecilerin eğitimi için örtülü ödenekten büyük bir kaynak ayırdığını belirterek, "Suriyeli mültecilere şimdiye dek

Figure 1. Article used in the Experiment

After reading the article, participants were asked to imagine that they are in a social media chat group composed of people who are between the ages of 18-30. They were randomly told that the group either consisted of pro-AKP or pro-CHP individuals. This means that participants would either have been placed in a context that can be labeled as 'like-minded' or as 'non-echo chamber' depending on their political affiliations (which were recorded in the initial questionnaire). The remainder of the participants were not told anything about the composition of the chat group (except the age of its members). Participants were then asked whether they would like to share the article with their imagined chat groups.

Participants were asked to fill in a post-treatment survey that, amongst other things, measured their arousal (to rule out the effect of arousal mechanisms, see Berger, 2011), partisanship and knowledge on the political topics that were measured in the pre-survey. They are asked to what extent they found the claims presented in the article to be believable in order to (albeit imperfectly) understand if anger changed their beliefs

regarding the veracity of the article. The subjects were also asked to what extent they support the policy options discussed in the article. Subjects were debriefed after the experiment to avoid false learning and dissemination of the false content to which they were exposed.

## A. Descriptive Results

## i. Party Support

Participants were asked if they feel close to a particular political party. Those who said yes were asked which party. Those who said no were asked whether they feel closer to a particular political party as compared to other parties. A significant majority of the sample supported CHP (78%). Iyi Party followed CHP in terms of popularity among the participants with 12% support. There were only 2 AKP supporters in the sample.

**TABLE 2. POLITICAL AFFILIATIONS** 

| Which political party do you feel close to? | Freq. | Percent |
|---|-------|---------|
| СНР   | 98    | 78.00   |
| IYI   | 15    | 12.00   |
| HDP   | 6     | 5.00    |
| MHP   | 3     | 2.00    |
| AKP   | 2     | 2.00    |
| Other                                       | 1     | 1.00    |
| Total                                       | 125   | 100.00  |

## ii. Anger and Echo Chamber

In both the anger treatment (46%) and control group (54%), the mean level of anger is 0.85 (See Appendix Table A1-A2 for the full tables). This indicates that the manipulation did not work properly. The average sharing rate in the treatment group is 40%.

TABLE 3A. ANGER

| Anger | Obs. | Anger Level | Shared |
|-------|------|-------------|--------|
| 0     | 57   | .859        | 38%    |
| 1     | 66   | .857        | 40%    |

Those who said that they felt close to CHP and were assigned to the treatment group that asked if the participants would like to share the article with CHP supporters (same procedure for AKP supporters) were coded as assigned to the echo chamber treatment (1=echo chamber, 0=non-echo chamber). The rest of the observations were dropped. The rate of willingness to share rate is 69% and 45% in the echo-chamber treatment and control groups, respectively. In the Anger + Echo chamber group, 54% of the participants were willing to share the article while the rate was only 44% in the No Anger + No Echo Chamber group (See Table A3 in the Appendix).

TABLE 3B. ECHO-CHAMBER

| Echo Chamber | Freq. | Percent | Shared |
|--------------|-------|---------|--------|
| 0            | 38    | 59.38   | 45%    |
| 1            | 26    | 40.62   | 69%    |

## B. Regression Results

The anger treatment does not produce any significant results in any of the models, which may be due to a failure to induce anger in the treatment group. However, echochamber treatment has a positive effect on the willingness to share. In Model 2, the participants in the echo chamber group were 24.5 percentage points more likely to share

the article in comparison to the control group. In model 3 below, those who were in the echo-chamber (but no anger) group were 40 percentage points more willing to share compared to those in the non-echo-chamber (and no anger) group. Contrary to my initial expectations, the Anger/Echo-chamber interaction does not produce a positive effect on the rate of sharing. Those who were assigned to the anger and echo-chamber treatment were less likely to say that they would share the article in their imagined echo-chamber, than those who received the echo-chamber treatment but not the anger treatment. However, this result is not statistically significant.

TABLE 4. ANGER AND ECHO-CHAMBER

| VARIABLES              | % Shared | % Shared | % Shared |
|------------------------|----------|----------|----------|
|                        |          |          |          |
| Anger                  | 0.0247   |          | 0.00556  |
|                        | (0.0890) |          | (0.167)  |
| Echo Chamber           |          | 0.245*   | 0.402**  |
|                        |          | (0.123)  | (0.159)  |
| Anger/Echo-<br>Chamber |          |          | -0.313   |
|                        |          |          | (0.243)  |
| Constant               | 0.379*** | 0.447*** | 0.444*** |
|                        | (0.0602) | (0.0820) | (0.121)  |
| Observations           | 123      | 64       | 64       |
| R-squared              | 0.001    | 0.058    | 0.097    |

Robust standard errors in parentheses \*\*\* p<0.01, \*\* p<0.05, \* p<0.1

## V. The Second Study

## A. Research Design

In the second experiment, subjects are recruited via the subject pool of the EssexLab at the University of Essex.<sup>20</sup> Upon arrival, participants were asked to complete a pre-test

<sup>&</sup>lt;sup>20</sup> The experiment was funded by the Scientific Research Council of Turkey and the EssexLab.

questionnaire to measure their attitudes on immigration, political affiliation, as well as various socio-economic characteristics. Following the survey, they were randomly assigned to either the anger or the control group and later were assigned to the likeminded/crosscutting and control groups for the chat groups. The experiment was conducted using the z-tree software package (Fischbacher, 2007). All participants received 8 GBP for their participation at the end of the experiment (4 GBP to show up plus 4 GBP for their time). All the hypotheses and the pre-analysis plan for the experiment are pre-registered<sup>21</sup> and the University of Essex gave ethical approval for the research.<sup>22</sup>

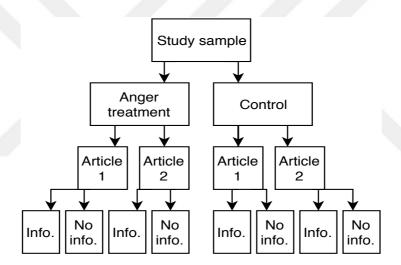


Figure 2. Experimental Design

Figure 2 presents the main experimental design. Participants who were randomly assigned to the 'anger groups' were asked to write down a political and then a personal issue that made them angry in the past. The purpose of these questions is to induce a 'state of anger'. They were asked to describe what made them angry and why.

<sup>&</sup>lt;sup>21</sup> More information on the registration is available here: http://egap.org/registration/5752

<sup>&</sup>lt;sup>22</sup> IRB reference number: 18/GV/164/AS

All study participants were then asked to read a misleading news article about immigration. The article assignment was randomized. After having read the article, subjects were told that they are assigned to a chat group with another participant in the experiment who either holds congruent or opposing views on immigration (Information treatment). The control group received a message that did not include any information regarding the political attitude of the other participant. The attitudes of the participants were measured in the pre-treatment survey as the participants answered the following question: "Do you think the number of immigrants in the UK should be increased a lot/be increased a little / remain as it is / be decreased a little / be decreased a lot...". Those who said that the number of immigrants should be increased were classified as pro-immigration and the rest of the participants were classified as anti-immigration. The allocation of the information treatment was randomized, so the participants were randomly assigned to either a like-minded or cross-cutting group, and the pre-treatment survey allowed me to inform the participants about their chat partner's attitudes without any deception.

As a result, the subject was either randomly assigned to a like-minded or an oppositional individual which simulates an echo-chamber or cross-cutting environment, respectively. The participants were also told that the other participant in the chat group had read a different article than them, but on the same policy issue (immigration). Finally, the participants were told that they could share what they read with the other participant or discuss what the other participant read or opt to stay silent.

| Treatment messages                                  | Control group message                              |  |  |
|---|--|--|--|
| In the next stage, you will be assigned to a chat   | In the next stage, you will be assigned to a chat  |  |  |
| group with another participant who shares/does      | group with another participant. The other          |  |  |
| <b>not share</b> your attitudes on immigration. The | participant read a different article on the same   |  |  |
| other participant read a different article on the   | subject. You may talk about your article, discuss  |  |  |
| same subject. You may talk about your article,      | what they read, or choose to remain silent. If you |  |  |
| discuss what they read, or choose to remain silent. | choose to remain silent, please inform the other   |  |  |
| If you choose to remain silent, please inform the   | participant about your decision.                   |  |  |
| other participant about your decision.              |  |  |  |
|   |  |  |  |

Following this message, which was on the screen for 45 seconds, the participants were assigned to the chat groups. After the chat groups, they were given other outcome questions such as the perceived accuracy of the article as well as demographics. At the end of the experiments, all participants were informed that the articles they read were misleading.

## B. Variables

## I. Treatments

The main independent variables are anger and attitude information treatments (like-minded/cross-cutting). Table 5 below shows that among the 234 participants, 126 received the anger treatment, and 108 were assigned to the control group. In total, 128 participants were assigned to the information treatment (like-minded or cross-cutting), and 106 were assigned to the control group.

TABLE 5. THE TREATMENTS

| Anger       | Frequency | Percent |
|-------------|-----------|---------|
| 0           | 108       | 46.15   |
| 1           | 126       | 53.85   |
| Information |           |         |
| 0           | 106       | 45.30   |
| 1           | 128       | 54.70   |
| Total       | 234       | 100.00  |

Among the participants who were assigned to the information treatment group, 66 received the likeminded message, and 62 received the cross-cutting message. A total of 106 participants were assigned to the control group.

TABLE 6. LIKE-MINDED MESSAGE

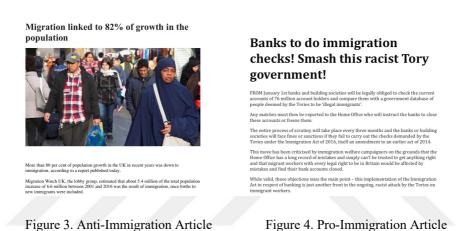
| Likeminded | Frequency | Percent |
|------------|-----------|---------|
| 0          | 50        | 43.10   |
| 1          | 66        | 56.90   |
| Total      | 116       | 100.00  |

TABLE 7. CROSSCUTTING MESSAGE

| Crosscutting | Frequency | Percent |
|--------------|-----------|---------|
| 0            | 56        | 47.46   |
| 1            | 62        | 52.54   |
| Total        | 118       | 100.00  |

Participants were randomly assigned to one of the articles. Half of the participants (117) received a pro-immigration article that was published by the website 'The News Line', and the other half received an article that included research done by

an anti-immigration lobby group in the UK that was published by the Times (Ford, 2018). The pro-immigration article was outdated and used unprofessional language and claimed that banks could do immigration checks (The News Line, 2017). The anti-immigration article was more neutral in its tone, but the statistics included in the article were rated as "misleading" by a fact-checking organization in the UK (Fullfact, 2018). A snapshot of the articles is provided below (See the references for the links to the full articles).



## II. Outcomes

The primary dependent variable in the experiment is 'the sharing of false information' in the chat group. This variable is coded as a binary variable. The participants were coded as 1 if they shared some information (such as statistics or the main message from the article they read). They were coded as 0 if they refused to share any information, stayed silent or just said the article was about immigration.

The chat group allows me to create multiple dependent variables through which we can identify secondary mechanisms behind sharing false information. Therefore, I created three other dependent variables—discussion, mentioning immigration, and willingness to talk. The chat groups also enabled me to check whether or not the

participants behaved differently when they were told about the attitudes of the other chat participants. Thus, I coded three binary variables—pro-immigration, anti-immigration, and ambiguous—to evaluate whether or not the participants revealed their attitudes about immigration during the chat. All the variables are presented below.

The discussion variable is coded as one if the participants had a conversation about the article or immigration, in general, that was longer than at least four lines.

The immigration variable is coded as one if the participants mentioned immigration overall. Those who said for example, "my article was about immigration" received 1 for this variable but 0 for sharing false information because they did not share any specific information from the article.

All those who were willing to chat and said anything more than "Hi" received one for the willingness variable. The participants did not have to share any information from the article. This variable is important because some participants could be willing to talk and discuss the article but were discouraged by the other participants' lack of interest in the chat group.

**TABLE 8. OUTCOME VARIABLES** 

|             |  | Level of        |
|-------------|--|-----------------|
|             |  | Restriction     |
| Variables   |  | (1 Not          |
| variables   | Coding Criteria                                  | Restrictive – 4 |
|             |  | Very            |
|             |  | Restrictive)    |
| Discussion  | Debating about immigration for more than 4 lines | 4               |
| Sharing     | Sharing specific information from the article    | 3               |
| Immigration | Talking about immigration in general             | 2               |
| Willingness | The participant has to say more than "Hi"        | 1               |

The pro-anti-ambiguous variables are coded according to the revealed immigration attitudes of the participants in the chat groups. For instance, some participants stated that they are pro-immigration while others were less clear about their attitudes or refrained from explicitly stating their position all together. These participants received 1 for being ambiguous, whereas those who stated clearly whether or not they were pro or anti-immigration received 1 for the relevant variables (pro-immigration & anti-immigration) and 0 for the rest. The participants who were in between—meaning that they were writing sentences such as "I support legal immigrants, but there should be limits on ..." were coded as ambiguous.

**TABLE 9. OUTCOME VARIABLES** 

| Variable         | Obs. | Mean | Std. Dev. | Min. | Max. |
|------------------|------|------|-----------|------|------|
| Discussion       | 234  | .35  | .478      | 0    | 1    |
| Share            | 234  | .59  | .492      | 0    | 1    |
| Immigration      | 234  | .68  | .469      | 0    | 1    |
| Willingness      | 234  | .85  | .357      | 0    | 1    |
| Pro-Immigration  | 178  | .29  | .456      | 0    | 1    |
| Anti-immigration | 178  | .03  | .180      | 0    | 1    |
| Ambiguous        | 178  | .66  | .472      | 0    | 1    |

#### C. Results

## I. Main Results

Table 11 presents the results of the primary independent variables—anger and information about the attitudes of the chat group participants. The first model tests the effect of the anger treatment on the rate of sharing false information. The second model examines the effect of being told about the attitudes of the other participant in the chat

group. The third model looks into the interaction between anger and information. The fourth and fifth model tests the effect of anger on the sharing of like-minded/crosscutting information  $(H_1)$ .

First, I check whether the participants who were assigned to the anger condition felt angry. All the participants answered a question that asked which feeling they felt most strongly after the anger treatment (or after four distraction questions for the control group). Only 16 out of 126 participants in the anger group stated that they feel angry. This result indicates that the anger manipulation has not worked well.

**TABLE 10. ANGER TREATMENT** 

| Manipulation |       |         |
|--------------|-------|---------|
| Check        | Freq. | Percent |
| 0            | 110   | 87.3    |
| 1            | 16    | 12.7    |

I use linear probability models to analyze the effect of the treatments on my outcomes. Linear probability models provide simplicity and precision when interpreting regression results from randomized experiments (Deke, 2014). In all the models, the outcomes are coded as binary and OLS regressions are carried out.<sup>23</sup>

Being informed about the attitude of the other participant in the chat group reduces the rate of sharing false information, and this effect is statistically significant on a 90% confidence level. The participants who were informed about whether the other participant in the chat group is likeminded or oppositional were 12 percentage points less likely to share any information from the news article they read than the control group. I also checked whether the subjects were more likely to share information when

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<sup>&</sup>lt;sup>23</sup> Please see the Appendix for robustness checks using logistic regression.

the news article they read was in line with their previously measured attitudes on immigration. While the effect of anger on the sharing of like-minded false information (Prior Belief=1) is positive, it is not statistically significant.

TABLE 11. THE EFFECT OF ANGER AND ECHO-CHAMBERS ON SHARING

| VARIABLES    | Model 1  | Model 2  | Model 3  | Prior Belief=1 | Prior Belief=0 |
|--------------|----------|----------|----------|----------------|----------------|
| Anger        | -0.0661  |          | -0.0623  | 0.00567        | -0.145         |
|              | (0.0644) |          | (0.0925) | (0.0903)       | (0.0919)       |
| Information  |          | -0.121*  | -0.118   |                |                |
|              |          | (0.0640) | (0.0928) |                |                |
| Info#Anger   |          |          | -0.00673 |                |                |
|              |          |          | (0.128)  |                |                |
| Constant     | 0.630*** | 0.660*** | 0.694*** | 0.579***       | 0.686***       |
|              | (0.0467) | (0.0462) | (0.0664) | (0.0659)       | (0.0656)       |
|              |          |          |          |                |                |
| Observations | 234      | 234      | 234      | 122            | 112            |
| R-squared    | 0.005    | 0.015    | 0.020    | 0.000          | 0.022          |

Robust standard errors in parentheses

## II. Perceived accuracy

Table 12 shows the effect of the anger and information treatment on the perceived accuracy of the news article. Being told about the other chat participant's attitudes and the interaction between anger and this treatment positively affect the perceived accuracy of the articles; however, these results are not statistically significant. The subgroup analysis shows that those who were in the like-minded chat groups were more likely to perceive the news article as accurate (H<sub>4</sub>) while those in the cross-cutting groups were less likely to believe the article content.

TABLE 12. PERCEIVED ACCURACY OF THE NEWS ARTICLE

| Variables         | Model 1  | Model 2  | Model 3  | Like-    | Cross-   |
|-------------------|----------|----------|----------|----------|----------|
|                   |          |          |          | minded   | cutting  |
|                   |          |          |          |          |          |
| Anger             | -0.0357  |          | -0.0537  |          |          |
|                   | (0.0639) |          | (0.0953) |          |          |
| Information       |          | 0.0333   | 0.0114   | 0.0764   | -0.0138  |
|                   |          | (0.0641) | (0.0945) | (0.0922) | (0.0895) |
| Anger#Information |          |          | 0.0328   |          |          |
|                   |          |          | (0.129)  |          |          |
| Constant          | 0.639*** | 0.610*** | 0.633*** | 0.560*** | 0.643*** |
|                   | (0.0469) | (0.0474) | (0.0699) | (0.0696) | (0.0649) |
| Observations      | 234      | 231      | 234      | 116      | 118      |
| R-squared         | 0.001    | 0.001    | 0.003    | 0.006    | 0.000    |

Robust standard errors in parentheses

## **III. Secondary Outcomes**

I tested the effect of being told about the other participant's attitudes on immigration on secondary outcomes—Discussion, Mentioning Immigration, and Willingness to Chat.<sup>24</sup> While being informed about the other participant's attitudes increases the likelihood of discussion, the result is not statistically significant. This treatment, however, reduces the likelihood of mentioning immigration and willingness to chat. Information about

<sup>24</sup> The anger treatment does not cause any statistically significant effects on any of the outcome variables. Therefore, here I only report further tests on the second model (Information treatment). The regression tables that include all the models are provided in the Appendix.

the attitude of the other participant reduces the rate of chatting and talking about immigration.

**TABLE 13. SECONDARY OUTCOMES** 

| VARIABLES    | Discussion | Immigration | Willingness |  |
|--------------|------------|-------------|-------------|--|
|              |            |             |             |  |
| Information  | 0.0887     | -0.128**    | -0.101**    |  |
|              | (0.0623)   | (0.0606)    | (0.0453)    |  |
| Constant     | 0.302***   | 0.745***    | 0.906***    |  |
|              | (0.0448)   | (0.0425)    | (0.0285)    |  |
| Observations | 234        | 234         | 234         |  |
| R-squared    | 0.009      | 0.019       | 0.020       |  |
|              |            |             |             |  |

Robust standard errors in parentheses \*\*\* p<0.01, \*\* p<0.05, \* p<0.1

Given that this negative effect may be driven by the participants assigned to cross-cutting chat groups, I ran another set of regressions on the observations from those who were assigned to these groups. Table 14 demonstrates the effect of being told that "the other participant does not share your attitudes on immigration." Those who were in cross-cutting chat groups were 15.5 percentage points less likely to mention the topic of immigration in their conversations and 17.2 percentage points less likely to be willing to chat overall. There are no statistically significant results for the like-minded groups (See Appendix Table B4).

TABLE 14. THE EFFECT OF CROSS-CUTTING GROUPS

| VARIABLES    | Share    | Discussion | Immigration | Willingness |
|--------------|----------|------------|-------------|-------------|
|              |          |            |             |             |
| Information  | -0.130   | 0.0691     | -0.155*     | -0.172***   |
|              | (0.0896) | (0.0864)   | (0.0844)    | (0.0616)    |
| Constant     | 0.679*** | 0.286***   | 0.768***    | 0.946***    |
|              | (0.0629) | (0.0609)   | (0.0569)    | (0.0303)    |
| Observations | 118      | 118        | 118         | 118         |
| R-squared    | 0.018    | 0.005      | 0.028       | 0.060       |
|              | D 1      |            |             |             |

Robust standard errors in parentheses

## IV. Attitudes on Immigration

Table 15 demonstrates the effect of the information treatment on the likelihood of sharing immigration attitudes in the chat groups. The participants who received information about the other participant's attitudes were more likely to reveal that they were pro-immigration by 14.8 percentage points and less likely to remain ambiguous by 13.9 percentage points.

TABLE 15. SHARING ATTITUDES ABOUT IMMIGRATION

| VARIABLES    | Pro-Immigration       | Anti-Immigration | Ambiguous |
|--------------|-----------------------|------------------|-----------|
|              |                       |                  |           |
| Information  | 0.148**               | 0.00152          | -0.139*   |
|              | (0.0679)              | (0.0272)         | (0.0704)  |
| Constant     | 0.220***              | 0.0330*          | 0.736***  |
|              | (0.0437)              | (0.0188)         | (0.0465)  |
| Observations | 178                   | 178              | 178       |
| R-squared    | 0.026                 | 0.000            | 0.022     |
| _            | Robust standard error |                  |           |

Robust standard errors in parentheses
\*\*\* p<0.01, \*\* p<0.05, \* p<0.1

I tested the effect of the information treatment on the group that received the 'like-minded' information. This information increases the propensity to share pro-immigration attitudes by 26.1 percentage points and decreases the ambiguity by 27.5 percentage points. This finding may be due to participants feeling more comfortable in like-minded groups and thereby revealing that they are pro-immigration.

TABLE 16. THE EFFECT OF "LIKEMINDED" CHAT GROUP INFORMATION

| VARIABLES    | Pro-Immigration | Anti-Immigration | Ambiguous |  |
|--------------|-----------------|------------------|-----------|--|
|              |                 |                  |           |  |
| Information  | 0.261***        | 0.0148           | -0.275*** |  |
|              | (0.0919)        | (0.0367)         | (0.0944)  |  |
| Constant     | 0.171**         | 0.0244           | 0.805***  |  |
|              | (0.0594)        | (0.0244)         | (0.0626)  |  |
| Observations | 92              | 92               | 92        |  |
| R-squared    | 0.078           | 0.002            | 0.083     |  |

Robust standard errors in parentheses

## VI. Conclusion

Disinformation on social media sites has become a major concern for democratic governance. As more people access the news via social media sites (Newman et al., 2018), it is vital to explore the psychological motivations behind sharing online news. In this study, I tested whether anger and likeminded clusters affect the sharing of false information on social media in two lab experiments conducted in Turkey and the United Kingdom. To the best of my knowledge, as the first study to show the underlying psychological motivations for the actual sharing of false information in online environments, this paper can advance our understanding of why inaccurate stories—including false news—quickly diffuse on social media sites.

In both studies, I first induced anger on randomly selected participants and made all participants read news articles. In the first study, the participants then answered questions that measured their willingness to share a false news article with imagined partisan groups on social media. In the second study, after reading a misleading news article about immigration, all participants were assigned to chat groups to observe whether or not they share false/misleading information they read. Before the chat assignment, some of the participants received information about the attitude (likeminded/crosscutting or control) of the other chat group participant. The second study allowed me to observe the actual sharing behavior, which is otherwise commonly measured with proxies such as 'willingness to share' (for example, see Guess et al., 2019).

In both studies, I am unable to induce anger among the participants in the treatment groups and observe no statistically significant effects of this treatment. As for the echo-chamber/cross-cutting treatment, the results are more complex. In the first study, I find that when subjects are told to imagine a social media group with likeminded partisans, they are more willing to share false news articles. In the second study, however, being told about the other participants' attitudes reduces the likelihood of sharing false information by 12.1 percentage points. The information treatment that informs the participant of whether or not the other participant in the chat group is likeminded/crosscutting affects the sharing behavior negatively. Furthermore, this treatment reduces the willingness to chat by 10.1 percentage points and talking about immigration in the chat groups by 12.8 percentage points. The crosscutting chat groups may drive this effect, given that the participants were less likely to willing to chat in these groups. Finally, while the information treatment increases the propensity to discuss the article content in the chat groups, the effect is not statistically significant.

Furthermore, the information treatment affects the participants' propensity to explicitly reveal their pro-immigration attitudes. The effect size of this treatment is even

larger for the participants in like-minded groups. These participants were also much less likely to be ambiguous about their attitudes in the chat group discussions. This finding may indicate that the participants who self-identify as pro-immigration felt more comfortable when they were told that they were in like-minded groups and thus shared their attitudes with the other participant.

Another outcome of interest in this study is the perceived accuracy of the news articles that the participants read. While the treatments do not have any statistically significant results in any of the models, the participants who received the information treatments were more likely to perceive the articles as accurate. The participants who were in like-minded groups were more likely to perceive the articles as accurate, whereas those in cross-cutting groups were less likely to say that the articles were accurate in comparison to the control group.

The failure to induce anger in both studies is noteworthy. In both studies, the chosen method of anger induction may not be working correctly, even though autobiographical recall is one of the most commonly used methods in psychology (Lobbestael et al., 2008).

The second treatment—being in like-minded/crosscutting environments—has contradictory effects on the sharing behavior. This result may be due to mainly three reasons. First, there may be a meaningful difference between "willingness to share" and the real sharing behavior. In the first study, the participants were told to imagine that they were in a social media environment with another participant who voted for a specific political party and asked if they would be willing to share the article with these people. Whereas in the second experiment, in which I measured the actual sharing behavior through a chat group interaction, I did not find the same result. Being told whether the other participant in the chat group was likeminded did not increase the

sharing of false information. Secondly, echo-chambers on social media sites may not be increasing the sharing of false information but have other effects on the behavior of social media users. For instance, like-minded environments may be facilitating some conversations but simultaneously leading to self-censorship among other participants. Finally, there may be a difference in the sample composition or the cultural context of Turkey and the United Kingdom.

Another potentially important factor that may have affected the results is the difference between a laboratory environment where participants cannot choose the article they would prefer to read and a real social media site where participants have countless options. Future research examining the effect of emotional states on news choice and the sharing behavior would help us get a better understanding of online news consumption.

There are several ways that this study contributes to our understanding of mis/disinformation. First, the study is conducted in two countries that are politically and culturally different from each other. Secondly, the study measures both people's willingness to share and their actual sharing behavior and demonstrates the difference between the two variables. However, there are some limitations to this study. First, both studies were conducted as lab experiments with student samples, which limits the generalizability of the findings. However, the experiments were conducted in two different settings, which help us compare the results and make better conclusions than a single lab experiment. A field study in which emotional states of the subjects could be measured frequently during a specific period to be examined in terms of their association with news consumption and sharing could contribute to our understanding.

## **APPENDIX**

TABLE A1. ANGER LEVELS

| Anger | Mean | Std. Dev. |
|-------|------|-----------|
| 0     | .859 | .35       |
| 1     | .857 | .353      |

TABLE A2. ECHO-CHAMBER

| Shared | Obs. | Mean | Std. Dev. |
|--------|------|------|-----------|
| Echo=1 | 26   | .692 | .47       |
| Echo=0 | 38   | .447 | .503      |

TABLE A3. ANGER AND ECHO-CHAMBER INTERACTION

| Variables     | Obs. | Shared | Std. Dev. |
|---------------|------|--------|-----------|
| Anger##Echo=1 | 13   | 54%    | .518      |
| Anger##Echo=0 | 18   | 44%    | .511      |

TABLE B1. DISCUSSION

| VARIABLES         | Model 1  | Model 2  | Model 3  |
|-------------------|----------|----------|----------|
| Anger             | 0.0146   |          | 0.0680   |
|                   | (0.0628) |          | (0.0895) |
| Information       |          | 0.0887   | 0.141    |
|                   |          | (0.0623) | (0.0906) |
| Anger#Information |          |          | -0.0980  |
|                   |          |          | (0.125)  |
| Constant          | 0.343*** | 0.302*** | 0.265*** |
|                   | (0.0459) | (0.0448) | (0.0636) |
| Observations      | 234      | 234      | 234      |
| R-squared         | 0.000    | 0.009    | 0.011    |

Robust standard errors in parentheses \*\*\* p<0.01, \*\* p<0.05, \* p<0.1

TABLE B2. IMMIGRATION

| VARIABLES            | Model 1  | Model 2  | Model 3  |
|----------------------|----------|----------|----------|
| Anger                | 0.0159   |          | 0.0956   |
|                      | (0.0617) |          | (0.0859) |
| Information          |          | -0.128** | -0.0498  |
|                      |          | (0.0606) | (0.0915) |
| Anger ## Information |          |          | -0.145   |
|                      |          |          | (0.122)  |
| Constant             | 0.667*** | 0.745*** | 0.694*** |
|                      | (0.0456) | (0.0425) | (0.0664) |
| Observations         | 234      | 234      | 234      |
| R-squared            | 0.000    | 0.019    | 0.025    |

Robust standard errors in parentheses \*\*\* p<0.01, \*\* p<0.05, \* p<0.1

TABLE B3. WILLINGNESS TO CHAT

| VARIABLES    | Model 1  | Model 2  | Model 3  |
|--------------|----------|----------|----------|
|              | -0.00265 |          |          |
| Anger        | (0.0469) |          | -0.0236  |
|              |          | -0.101** | (0.0569) |
| Info         |          | (0.0453) | -0.122*  |
|              |          |          | (0.0660) |
| Anger#Info   |          |          | 0.0386   |
|              |          |          | (0.0910) |
| Constant     | 0.852*** | 0.906*** | 0.918*** |
|              | (0.0343) | (0.0285) | (0.0395) |
|              |          |          |          |
| Observations | 234      | 234      | 234      |
| R-squared    | 0.000    | 0.020    | 0.021    |
|              |          |          |          |

Robust standard errors in parentheses

\*\*\* p<0.01, \*\* p<0.05, \* p<0.1

TABLE B4. SECONDARY OUTCOMES IN LIKEMINDED CHAT GROUPS

| VARIABLES    | Discussion | Share    | Immigration | Willingness |
|--------------|------------|----------|-------------|-------------|
|              |            |          |             |             |
| Information  | 0.104      | -0.110   | -0.0988     | -0.0267     |
|              | (0.0912)   | (0.0929) | (0.0889)    | (0.0684)    |
| Constant     | 0.320***   | 0.640*** | 0.720***    | 0.860***    |
|              | (0.0688)   | (0.0700) | (0.0670)    | (0.0516)    |
| Observations | 116        | 116      | 116         | 116         |
| R-squared    | 0.011      | 0.012    | 0.011       | 0.001       |
|              |            |          |             |             |

Robust standard errors in parentheses

\*\*\* p<0.01, \*\* p<0.05, \* p<0.1

TABLE C1. PRO-IMMIGRATION

| VARIABLES         | Model 1  | Model 2  | Model 3  |
|-------------------|----------|----------|----------|
|                   | 0.0179   |          |          |
| Anger             | (0.0689) |          | -0.00931 |
|                   |          |          | (0.0886) |
| Information       |          | 0.148**  | 0.117    |
|                   |          | (0.0679) | (0.103)  |
| Anger#Information |          |          | 0.0550   |
|                   |          |          | (0.137)  |
| Constant          | 0.282*** | 0.220*** | 0.225*** |
|                   | (0.0512) | (0.0437) | (0.0668) |
|                   |          |          |          |
| Observations      | 178      | 178      | 178      |
| R-squared         | 0.000    | 0.026    | 0.028    |
|                   |          |          |          |

Robust standard errors in parentheses
\*\*\* p<0.01, \*\* p<0.05, \* p<0.1

TABLE C2. ANTI-IMMIGRATION

| VARIABLES         | Model 1  | Model 2  | Model 3  |
|-------------------|----------|----------|----------|
|                   |          |          |          |
| Anger             | -0.00846 |          | 0.0142   |
|                   | (0.0278) |          | (0.0371) |
| Information       |          | 0.00152  | 0.0276   |
|                   |          | (0.0272) | (0.0443) |
| Anger#Information |          |          | -0.0464  |
|                   |          |          | (0.0560) |
| Constant          | 0.0385*  | 0.0330*  | 0.0250   |
|                   | (0.0219) | (0.0188) | (0.0250) |
|                   |          |          |          |
| Observations      | 178      | 178      | 178      |
| R-squared         | 0.001    | 0.000    | 0.005    |
|                   |          |          |          |

Robust standard errors in parentheses \*\*\* p<0.01, \*\* p<0.05, \* p<0.1

TABLE C3. AMBIGUOUS

| VARIABLES         | Model 1  | Model 2  | Model 3  |
|-------------------|----------|----------|----------|
|                   | -0.0195  |          |          |
| Anger             | (0.0714) |          | -0.0245  |
|                   |          | -0.139*  | (0.0938) |
| Information       |          | (0.0704) | -0.145   |
|                   |          |          | (0.106)  |
| Anger#Information |          |          | 0.0111   |
|                   |          |          | (0.142)  |
| Constant          | 0.679*** | 0.736*** | 0.750*** |
|                   | (0.0531) | (0.0465) | (0.0692) |
|                   |          |          |          |
| Observations      | 178      | 178      | 178      |
| R-squared         | 0.000    | 0.022    | 0.022    |

Robust standard errors in parentheses
\*\*\* p<0.01, \*\* p<0.05, \* p<0.1

# **Robustness checks**

## 1. Outcome: Sharing

| share              | Coef.  | St.Err. | t-       | p-            | [95%   | Interval] | Sig |
|--------------------|--------|---------|----------|---------------|--------|-----------|-----|
|                    |        |         | value    | value         | Conf   |           |     |
| treatAnger         | -0.275 | 0.268   | -1.03    | 0.305         | -0.801 | 0.251     |     |
| Constant           | 0.531  | 0.199   | 2.66     | 0.008         | 0.140  | 0.921     | *** |
| Mean dependent var |        | 0.594   | SD depe  | endent var    |        | 0.492     |     |
| Pseudo r-squared   |        | 0.003   | Number   | of obs        |        | 234.000   |     |
| Chi-square         |        | 1.057   | Prob > c | ehi2          |        | 0.304     |     |
| Akaike crit. (AIC) |        | 319.013 | Bayesia  | n crit. (BIC) |        | 325.923   |     |
|                    |        |         |          |               |        |           |     |

<sup>\*\*\*</sup> p<0.01, \*\* p<0.05, \* p<0.1

| 8 0.271<br>5 0.205 | -1.88<br>3.24  | value<br>0.061<br>0.001   | Conf<br>-1.040<br>0.263                  | 0.023                                    | *  |
|--------------------|----------------|---------------------------|--|--|--|
| -                  |                |                           |  |  |  |
| 5 0.205            | 3.24           | 0.001                     | 0.262                                    | 1.067                                    |  |
|                    |                | 0.001                     | 0.203                                    | 1.067                                    | ***  |
| 0.594              | SD dep         | endent var                |  | 0.492                                    |  |
| 0.011              | Number         | r of obs                  |  | 234.000                                  |  |
| 3.560              | Prob >         | chi2                      |  | 0.059                                    |  |
| 316.510            | Bayesia        | in crit. (BIC)            |  | 323.421                                  |  |
|                    | 0.011<br>3.560 | 0.011 Number 3.560 Prob > | 0.011 Number of obs<br>3.560 Prob > chi2 | 0.011 Number of obs<br>3.560 Prob > chi2 | 0.011 Number of obs 234.000<br>3.560 Prob > chi2 0.059 |

<sup>\*\*\*</sup> p<0.01, \*\* p<0.05, \* p<0.1

**Logistic regression** 

| share              | Coef.  | St.Err. | t-       | p-            | [95%   | Interval] | Sig |
|--------------------|--------|---------|----------|---------------|--------|-----------|-----|
|                    |        |         | value    | value         | Conf   |           |     |
| 0b.treatAnger      | 0.000  |         |          |               | •      |           |     |
| 1.treatAnger       | -0.279 | 0.414   | -0.68    | 0.500         | -1.091 | 0.532     |     |
| 0b.treatInfo       | 0.000  |         |          |               |        |           |     |
| 1.treatInfo        | -0.511 | 0.407   | -1.26    | 0.209         | -1.308 | 0.286     |     |
|                    | 0.000  |         |          |               |        |           |     |
| 0b.treatAnger#0    |        |         |          |               |        |           |     |
| b.t~o              |        |         |          |               |        |           |     |
|                    | 0.000  |         |          |               |        |           |     |
| 0b.treatAnger#1    |        |         |          |               |        |           |     |
| o.t~o              |        |         |          |               |        |           |     |
|                    | 0.000  |         |          |               |        |           |     |
| 1o.treatAnger#0    |        |         |          |               |        |           |     |
| b.t~o              |        |         |          |               |        |           |     |
|                    | 0.001  | 0.547   | 0.00     | 0.999         | -1.071 | 1.072     |     |
| 1.treatAnger#1.t   |        |         |          |               |        |           |     |
| re~o               |        |         |          |               |        |           |     |
| Constant           | 0.818  | 0.310   | 2.64     | 0.008         | 0.211  | 1.426     | *** |
| Mean dependent var |        | 0.594   | SD depe  | endent var    |        | 0.492     |     |
| Pseudo r-squared   |        | 0.015   | Number   | of obs        |        | 234.000   |     |
| Chi-square         |        | 4.628   | Prob > c | chi2          |        | 0.201     |     |
| Akaike crit. (AIC) |        | 319.442 | Bavesia  | n crit. (BIC) |        | 333.263   |     |

<sup>\*\*\*</sup> p<0.01, \*\* p<0.05, \* p<0.1

| share               | Coef. | St.Err. | t-       | p-             | [95%   | Interval] | Sig |
|---------------------|-------|---------|----------|----------------|--------|-----------|-----|
|                     |       |         | value    | value          | Conf   |           |     |
| treatAnger          | 0.023 | 0.369   | 0.06     | 0.950          | -0.701 | 0.747     |     |
| Constant            | 0.318 | 0.269   | 1.18     | 0.237          | -0.210 | 0.846     |     |
| Mean dependent var  |       | 0.582   | SD depe  | endent var     |        | 0.495     |     |
| Pseudo r-squared    |       | 0.000   | Number   | of obs         |        | 122.000   |     |
| Chi-square          |       | 0.004   | Prob > c | hi2            |        | 0.950     |     |
| Akaike crit. (AIC)  |       | 169.830 | Bayesia  | n crit. (BIC)  |        | 175.438   |     |
| rikaike crit. (AIC) |       | 107.030 | Dayesia  | ii ciii. (Dic) |        | 173.436   |     |

<sup>\*\*\*</sup> p<0.01, \*\* p<0.05, \* p<0.1

| share              | Coef.  | St.Err. | t-       | p-            | [95%   | Interval] | Sig |
|--------------------|--------|---------|----------|---------------|--------|-----------|-----|
|                    |        |         | value    | value         | Conf   |           |     |
| treatAnger         | -0.618 | 0.398   | -1.55    | 0.120         | -1.399 | 0.162     |     |
| Constant           | 0.783  | 0.303   | 2.58     | 0.010         | 0.189  | 1.377     | **  |
| Mean dependent var |        | 0.607   | SD depe  | endent var    |        | 0.491     |     |
| Pseudo r-squared   |        | 0.017   | Number   | of obs        |        | 112.000   |     |
| Chi-square         |        | 2.413   | Prob > c | hi2           |        | 0.120     |     |
| Akaike crit. (AIC) |        | 151.603 | Bayesia  | n crit. (BIC) |        | 157.040   |     |

<sup>\*\*\*</sup> p<0.01, \*\* p<0.05, \* p<0.1

# 2. Outcome: Perceived Accuracy

| accuracy           | Coef. | St.Err. | t-       | p-            | [95%   | Interval] | Sig |
|--------------------|-------|---------|----------|---------------|--------|-----------|-----|
|                    |       |         | value    | value         | Conf   |           |     |
| treatInfo          | 0.142 | 0.273   | 0.52     | 0.602         | -0.393 | 0.678     |     |
| Constant           | 0.445 | 0.200   | 2.23     | 0.026         | 0.053  | 0.837     | **  |
| Mean dependent var |       | 0.628   | SD depe  | endent var    |        | 0.484     |     |
| Pseudo r-squared   |       | 0.001   | Number   | of obs        |        | 231.000   |     |
| Chi-square         |       | 0.272   | Prob > c | chi2          |        | 0.602     |     |
| Akaike crit. (AIC) |       | 308.724 | Bayesia  | n crit. (BIC) |        | 315.609   |     |
|                    |       |         |          |               |        |           |     |

<sup>\*\*\*</sup> p<0.01, \*\* p<0.05, \* p<0.1

| accuracy             | Coef.  | St.Err. | t-       | p-            | [95%   | Interval] | Sig |
|----------------------|--------|---------|----------|---------------|--------|-----------|-----|
|                      |        |         | value    | value         | Conf   | _         |     |
| 0b.treatAnger        | 0.000  |         |          | •             |        |           |     |
| 1.treatAnger         | -0.225 | 0.400   | -0.56    | 0.573         | -1.009 | 0.558     |     |
| 0b.treatInfo         | 0.000  |         |          | •             |        | •         |     |
| 1.treatInfo          | 0.049  | 0.402   | 0.12     | 0.902         | -0.739 | 0.838     |     |
|                      | 0.000  |         | •        |               |        |           |     |
| 0b.treatAnger#0      |        |         |          |               |        |           |     |
| b.t∼o                |        |         |          |               |        |           |     |
|                      | 0.000  |         |          | •             |        | •         |     |
| 0b.treatAnger#1      |        |         |          |               |        |           |     |
| o.t~o                |        |         |          |               |        |           |     |
|                      | 0.000  |         | •        |               |        |           |     |
| 1o.treatAnger#0      |        |         |          |               |        |           |     |
| b.t∼o                |        |         |          |               |        |           |     |
|                      | 0.135  | 0.544   | 0.25     | 0.804         | -0.930 | 1.201     |     |
| 1.treatAnger#1.t     |        |         |          |               |        |           |     |
| re~o                 |        |         |          |               |        |           |     |
| Constant             | 0.544  | 0.296   | 1.83     | 0.067         | -0.037 | 1.124     | *   |
| Maan dan an dant wan |        | 0.620   | CD done  | and ant year  |        | 0.497     |     |
| Mean dependent var   |        | 0.620   |          | endent var    |        | 0.487     |     |
| Pseudo r-squared     |        | 0.002   | Number   |               |        | 234.000   |     |
| Chi-square           |        | 0.585   | Prob > c |               |        | 0.900     |     |
| Akaike crit. (AIC)   |        | 318.275 | Bayesia  | n crit. (BIC) |        | 332.096   |     |

<sup>\*\*\*</sup> p<0.01, \*\* p<0.05, \* p<0.1

**Logistic regression** 

| Accuracy           | Coef. | St.Err. | t-       | p-            | [95%   | Interval] | Sig |
|--------------------|-------|---------|----------|---------------|--------|-----------|-----|
| (Likeminded)       |       |         | value    | value         | Conf   |           |     |
| treatInfo          | 0.318 | 0.383   | 0.83     | 0.406         | -0.432 | 1.069     |     |
| Constant           | 0.241 | 0.285   | 0.85     | 0.397         | -0.317 | 0.800     |     |
| Mean dependent var |       | 0.603   | SD depe  | endent var    |        | 0.491     |     |
| Pseudo r-squared   |       | 0.004   | Number   | of obs        |        | 116.000   |     |
| Chi-square         |       | 0.692   | Prob > c | hi2           |        | 0.405     |     |
| Akaike crit. (AIC) |       | 159.117 | Bayesia  | n crit. (BIC) |        | 164.624   |     |
|                    |       |         |          |               |        |           |     |

<sup>\*\*\*</sup> p<0.01, \*\* p<0.05, \* p<0.1

| Accuracy           | Coef.  | St.Err. | t-       | p-            | [95%   | Interval] | Sig |
|--------------------|--------|---------|----------|---------------|--------|-----------|-----|
| (Cross-cutting)    |        |         | value    | value         | Conf   |           |     |
| treatInfo          | -0.060 | 0.383   | -0.16    | 0.876         | -0.811 | 0.691     |     |
| Constant           | 0.588  | 0.279   | 2.11     | 0.035         | 0.041  | 1.134     | **  |
|                    |        |         |          |               |        |           |     |
| Mean dependent var |        | 0.636   | SD depe  | ndent var     |        | 0.483     |     |
| Pseudo r-squared   |        | 0.000   | Number   | of obs        |        | 118.000   |     |
| Chi-square         |        | 0.024   | Prob > c | hi2           |        | 0.876     |     |
| Akaike crit. (AIC) |        | 158.771 | Bayesia  | n crit. (BIC) |        | 164.312   |     |
|                    |        |         |          |               |        |           |     |

<sup>\*\*\*</sup> p<0.01, \*\* p<0.05, \* p<0.1

# 3. Sub-group Analyses: Cross-cutting

**Logistic regression** 

| share              | Coef.  | St.Err. | t-       | p-            | [95%   | Interval] | Sig |
|--------------------|--------|---------|----------|---------------|--------|-----------|-----|
|                    |        |         | value    | value         | Conf   |           |     |
| treatInfo          | -0.553 | 0.385   | -1.44    | 0.151         | -1.308 | 0.202     |     |
| Constant           | 0.747  | 0.287   | 2.60     | 0.009         | 0.184  | 1.310     | *** |
| Mean dependent var |        | 0.610   | SD depe  | endent var    |        | 0.490     |     |
| Pseudo r-squared   |        | 0.013   | Number   | of obs        |        | 118.000   |     |
| Chi-square         |        | 2.063   | Prob > c | hi2           |        | 0.151     |     |
| Akaike crit. (AIC) |        | 159.698 | Bayesia  | n crit. (BIC) |        | 165.240   |     |

<sup>\*\*\*</sup> p<0.01, \*\* p<0.05, \* p<0.1

**Logistic regression** 

| discussion           | Coef.  | St.Err. | t-       | p-             | [95%   | Interval] | Sig |
|----------------------|--------|---------|----------|----------------|--------|-----------|-----|
|                      |        |         | value    | value          | Conf   |           |     |
| treatInfo            | 0.318  | 0.399   | 0.80     | 0.425          | -0.464 | 1.101     |     |
| Constant             | -0.916 | 0.297   | -3.08    | 0.002          | -1.499 | -0.334    | *** |
| Mean dependent var   |        | 0.322   | SD depe  | endent var     |        | 0.469     |     |
| Pseudo r-squared     |        | 0.004   | Number   | of obs         |        | 118.000   |     |
| Chi-square           |        | 0.637   | Prob > c | chi2           |        | 0.425     |     |
| Akaike crit. (AIC)   |        | 151.655 | Bayesia  | n crit. (BIC)  |        | 157.196   |     |
| rikaike erit. (rife) |        | 151.055 | Buyesia  | ii ciii. (Bie) |        | 157.170   |     |

<sup>\*\*\*</sup> p<0.01, \*\* p<0.05, \* p<0.1

**Logistic regression** 

| Coef.  | St.Err. | t-   | p-            | [95%                | Interval]               | Sig   |
|--------|---------|--|---------------|---------------------|-------------------------|---|
|        |         | value  | value         | Conf                |                         |   |
| -0.737 | 0.412   | -1.79  | 0.074         | -1.544              | 0.070                   | *   |
| 1.196  | 0.318   | 3.76   | 0.000         | 0.573               | 1.819                   | ***   |
|        | 0.686   | SD depe  | endent var    |                     | 0.466                   |   |
|        | 0.023   | Number   | of obs        |                     | 118.000                 |   |
|        | 3.200   | Prob > c   | hi2           |                     | 0.074                   |   |
|        | 147.449 | Bayesia  | n crit. (BIC) |                     | 152.990                 |   |
|        | -0.737  | -0.737 0.412<br>1.196 0.318<br>0.686<br>0.023<br>3.200 | value  -0.737 | value value  -0.737 | value value Conf -0.737 | value         value         Conf           -0.737         0.412         -1.79         0.074         -1.544         0.070           1.196         0.318         3.76         0.000         0.573         1.819           0.686         SD dependent var<br>0.023         0.466         118.000           3.200         Prob > chi2         0.074 |

<sup>\*\*\*</sup> p<0.01, \*\* p<0.05, \* p<0.1

| Coef.  | St.Err. | t-                                     | p-  | [95%   | Interval]   | Sig  |
|--------|---------|--|---|--|---|--|
|        |         | value                                  | value   | Conf   |   |  |
| -1.640 | 0.670   | -2.45                                  | 0.014   | -2.952   | -0.327  | **   |
| 2.872  | 0.596   | 4.82                                   | 0.000   | 1.704  | 4.040   | ***  |
|        | 0.856   | SD depe                                | endent var  |  | 0.353   |  |
|        | 0.079   | Number                                 | of obs  |  | 118.000   |  |
|        | 5.997   | Prob > c                               | hi2   |  | 0.014   |  |
|        | 93.633  | Bayesia                                | n crit. (BIC)   |  | 99.174  |  |
|        |         | 2.872 0.596<br>0.856<br>0.079<br>5.997 | -1.640 0.670 -2.45<br>2.872 0.596 4.82<br>0.856 SD depe<br>0.079 Number<br>5.997 Prob > c | -1.640 0.670 -2.45 0.014<br>2.872 0.596 4.82 0.000<br>0.856 SD dependent var<br>0.079 Number of obs<br>5.997 Prob > chi2 | -1.640 0.670 -2.45 0.014 -2.952<br>2.872 0.596 4.82 0.000 1.704<br>0.856 SD dependent var<br>0.079 Number of obs<br>5.997 Prob > chi2 | -1.640 0.670 -2.45 0.014 -2.952 -0.327<br>2.872 0.596 4.82 0.000 1.704 4.040<br>0.856 SD dependent var 0.353<br>0.079 Number of obs 118.000<br>5.997 Prob > chi2 0.014 |

<sup>\*\*\*</sup> p<0.01, \*\* p<0.05, \* p<0.1

# 4. Sub-group Analyses: Likeminded

Logistic regression

| share              | Coef.  | St.Err. | t-       | p-            | [95%   | Interval] | Sig |
|--------------------|--------|---------|----------|---------------|--------|-----------|-----|
|                    |        |         | value    | value         | Conf   |           |     |
| treatInfo          | -0.454 | 0.386   | -1.18    | 0.239         | -1.210 | 0.302     |     |
| Constant           | 0.575  | 0.296   | 1.94     | 0.052         | -0.005 | 1.155     | *   |
| Mean dependent var |        | 0.578   | SD depe  | endent var    |        | 0.496     |     |
| Pseudo r-squared   |        | 0.009   | Number   | of obs        |        | 116.000   |     |
| Chi-square         |        | 1.384   | Prob > c | hi2           |        | 0.239     |     |
| Akaike crit. (AIC) |        | 160.595 | Bayesia  | n crit. (BIC) |        | 166.102   |     |

<sup>\*\*\*</sup> p<0.01, \*\* p<0.05, \* p<0.1

**Logistic regression** 

| discussion         | Coef.  | St.Err. | t-                     | p-            | [95%    | Interval] | Sig |
|--------------------|--------|---------|------------------------|---------------|---------|-----------|-----|
|                    |        |         | value                  | value         | Conf    |           |     |
| treatInfo          | 0.448  | 0.394   | 1.14                   | 0.255         | -0.324  | 1.221     |     |
| Constant           | -0.754 | 0.304   | -2.48                  | 0.013         | -1.351  | -0.157    | **  |
| Mean dependent var |        | 0.379   | SD dependent var 0.487 |               |         |           |     |
| Pseudo r-squared   |        | 0.009   | •                      |               | 116.000 |           |     |
| Chi-square         |        | 1.295   | Prob > c               | chi2          |         | 0.255     |     |
| Akaike crit. (AIC) |        | 156.661 | Bayesia                | n crit. (BIC) | )       | 162.169   |     |
| *                  |        | 156.661 | Bayesia                | n crit. (BIC) | )       | 162.16    | 9   |

<sup>\*\*\*</sup> p<0.01, \*\* p<0.05, \* p<0.1

**Logistic regression** 

| immigration        | Coef.  | St.Err. | t-       | p-            | [95%   | Interval] | Sig |
|--------------------|--------|---------|----------|---------------|--------|-----------|-----|
| -                  |        |         | value    | value         | Conf   |           |     |
| treatInfo          | -0.450 | 0.406   | -1.11    | 0.268         | -1.246 | 0.346     |     |
| Constant           | 0.944  | 0.316   | 2.99     | 0.003         | 0.324  | 1.564     | *** |
| Mean dependent var |        | 0.664   | SD depe  | endent var    |        | 0.474     |     |
| Pseudo r-squared   |        | 0.008   | Number   | of obs        |        | 116.000   |     |
| Chi-square         |        | 1.226   | Prob > c | hi2           |        | 0.268     |     |
| Akaike crit. (AIC) |        | 150.873 | Bayesia  | n crit. (BIC) |        | 156.380   |     |

<sup>\*\*\*</sup> p<0.01, \*\* p<0.05, \* p<0.1

| willingness        | Coef.  | St.Err. | t-       | p-                    | [95%   | Interval] | Sig |
|--------------------|--------|---------|----------|-----------------------|--------|-----------|-----|
|                    |        |         | value    | value                 | Conf   |           |     |
| treatInfo          | -0.206 | 0.527   | -0.39    | 0.696                 | -1.239 | 0.827     |     |
| Constant           | 1.815  | 0.409   | 4.43     | 0.000                 | 1.013  | 2.618     | *** |
|                    |        |         |          |                       |        |           |     |
| Mean dependent var |        | 0.845   | SD depe  | SD dependent var 0.30 |        |           |     |
| Pseudo r-squared   |        | 0.002   | Number   | of obs                |        | 116.000   |     |
| Chi-square         |        | 0.153   | Prob > c | hi2                   |        | 0.696     |     |
| Akaike crit. (AIC) |        | 103.970 | Bayesia  | n crit. (BIC)         |        | 109.478   |     |
|                    |        |         |          |                       |        |           |     |

## 5. Revealed attitudes

Logistic regression

| Logistic regression |        |         |          |               |        |           |     |
|---------------------|--------|---------|----------|---------------|--------|-----------|-----|
| Pro-                | Coef.  | St.Err. | t-       | p-            | [95%   | Interval] | Sig |
| immigration         |        |         | value    | value         | Conf   |           |     |
| treatInfo           | 0.725  | 0.338   | 2.15     | 0.032         | 0.063  | 1.388     | **  |
| Constant            | -1.267 | 0.254   | -4.99    | 0.000         | -1.765 | -0.769    | *** |
| Mean dependent var  |        | 0.292   | SD depe  | endent var    |        | 0.456     |     |
| Pseudo r-squared    |        | 0.022   | Number   | of obs        |        | 178.000   |     |
| Chi-square          |        | 4.609   | Prob > c | chi2          |        | 0.032     |     |
| Akaike crit. (AIC)  |        | 214.301 | Bayesia  | n crit. (BIC) |        | 220.664   |     |
|                     |        |         |          |               |        |           |     |

<sup>\*\*\*</sup> p<0.01, \*\* p<0.05, \* p<0.1

Logistic regression

| Logistic regression |        |         |               |               |         |           |     |
|---------------------|--------|---------|---------------|---------------|---------|-----------|-----|
| Anti-               | Coef.  | St.Err. | t-            | p-            | [95%    | Interval] | Sig |
| immigration         |        |         | value         | value         | Conf    |           |     |
| treatInfo           | 0.047  | 0.833   | 0.06          | 0.955         | -1.586  | 1.679     |     |
| Constant            | -3.379 | 0.589   | -5.74         | 0.000         | -4.533  | -2.225    | *** |
|                     |        |         |               |               |         |           |     |
| Mean dependent var  |        | 0.034   | SD depe       | endent var    |         | 0.181     |     |
| Pseudo r-squared    |        | 0.000   | Number of obs |               | 178.000 |           |     |
| Chi-square          |        | 0.003   | Prob > c      | chi2          |         | 0.955     |     |
| Akaike crit. (AIC)  |        | 56.473  | Bayesia       | n crit. (BIC) |         | 62.836    |     |
|                     |        |         |               |               |         |           |     |

<sup>\*\*\*</sup> p<0.01, \*\* p<0.05, \* p<0.1

| Logistic regression |        |         |          |               |        |           |     |
|---------------------|--------|---------|----------|---------------|--------|-----------|-----|
| Ambiguous           | Coef.  | St.Err. | t-       | p-            | [95%   | Interval] | Sig |
|                     |        |         | value    | value         | Conf   |           |     |
| treatInfo           | -0.631 | 0.324   | -1.95    | 0.052         | -1.266 | 0.004     | *   |
| Constant            | 1.027  | 0.239   | 4.30     | 0.000         | 0.559  | 1.494     | *** |
| Mean dependent var  |        | 0.669   | SD depe  | endent var    |        | 0.472     |     |
| Pseudo r-squared    |        | 0.017   | Number   | of obs        |        | 178.000   |     |
| Chi-square          |        | 3.789   | Prob > c | chi2          |        | 0.052     |     |
| Akaike crit. (AIC)  |        | 226.265 | Bayesia  | n crit. (BIC) |        | 232.629   |     |
|                     |        |         |          |               |        |           |     |

<sup>\*\*\*</sup> p<0.01, \*\* p<0.05, \* p<0.1

# 6. Revealed attitudes: Likeminded groups

**Logistic regression** 

| pro2               | Coef.  | St.Err. | t-       | p-                     | [95%   | Interval] | Sig |
|--------------------|--------|---------|----------|------------------------|--------|-----------|-----|
|                    |        |         | value    | value                  | Conf   |           |     |
| treatInfo          | 1.304  | 0.505   | 2.58     | 0.010                  | 0.315  | 2.294     | **  |
| Constant           | -1.580 | 0.417   | -3.79    | 0.000                  | -2.398 | -0.763    | *** |
| Mean dependent var |        | 0.315   | SD depe  | SD dependent var 0.467 |        |           |     |
| Pseudo r-squared   |        | 0.065   | Number   | of obs                 |        | 92.000    |     |
| Chi-square         |        | 6.671   | Prob > c | hi2                    |        | 0.010     |     |
| Akaike crit. (AIC) |        | 111.215 | Bayesia  | n crit. (BIC)          |        | 116.258   |     |

<sup>\*\*\*</sup> p<0.01, \*\* p<0.05, \* p<0.1

Logistic regression

| anti2              | Coef.  | St.Err. | t-       | p-            | [95%   | Interval] | Sig |
|--------------------|--------|---------|----------|---------------|--------|-----------|-----|
| antiz              | Coci.  | St.LII. | =        | .*            | L      | micivaij  | Sig |
|                    |        |         | value    | value         | Conf   |           |     |
| treatInfo          | 0.490  | 1.250   | 0.39     | 0.695         | -1.960 | 2.940     |     |
| Constant           | -3.689 | 1.018   | -3.62    | 0.000         | -5.684 | -1.694    | *** |
|                    |        | / /     |          |               |        |           |     |
| Mean dependent var |        | 0.033   | SD depe  | endent var    |        | 0.179     |     |
| Pseudo r-squared   |        | 0.006   | Number   | of obs        |        | 92.000    |     |
| Chi-square         |        | 0.154   | Prob > c | hi2           |        | 0.695     |     |
| Akaike crit. (AIC) |        | 30.278  | Bayesia  | n crit. (BIC) |        | 35.321    |     |
|                    |        |         |          |               |        |           |     |

<sup>\*\*\*</sup> p<0.01, \*\* p<0.05, \* p<0.1

| ambig2             | Coef.  | St.Err. | t-       | p-            | [95%   | Interval] | Sig |
|--------------------|--------|---------|----------|---------------|--------|-----------|-----|
|                    |        |         | value    | value         | Conf   |           |     |
| treatInfo          | -1.299 | 0.486   | -2.67    | 0.008         | -2.253 | -0.346    | *** |
| Constant           | 1.417  | 0.396   | 3.58     | 0.000         | 0.640  | 2.194     | *** |
| Mean dependent var |        | 0.652   | SD depe  | endent var    | 0.479  |           |     |
| Pseudo r-squared   |        | 0.066   | Number   | of obs        |        | 92.000    |     |
| Chi-square         |        | 7.136   | Prob > c | hi2           |        | 0.008     |     |
| Akaike crit. (AIC) |        | 114.997 | Bayesia  | n crit. (BIC) |        | 120.040   |     |
|                    |        |         |          |               |        |           |     |

<sup>\*\*\*</sup> p<0.01, \*\* p<0.05, \* p<0.1

# 7. Revealed attitudes: Crosscutting groups

**Logistic regression** 

| pro2               | Coef.  | St.Err. | t-       | p-                     | [95%   | Interval] | Sig |
|--------------------|--------|---------|----------|------------------------|--------|-----------|-----|
|                    |        |         | value    | value                  | Conf   |           |     |
| treatInfo          | 0.090  | 0.495   | 0.18     | 0.855                  | -0.880 | 1.061     |     |
| Constant           | -1.046 | 0.324   | -3.23    | 0.001                  | -1.682 | -0.410    | *** |
| Mean dependent var |        | 0.267   | SD depe  | SD dependent var 0.445 |        |           |     |
| Pseudo r-squared   |        | 0.000   | Number   | Number of obs 86.00    |        |           |     |
| Chi-square         |        | 0.033   | Prob > c | hi2                    |        | 0.855     |     |
| Akaike crit. (AIC) |        | 103.846 | Bayesia  | n crit. (BIC)          |        | 108.755   |     |

<sup>\*\*\*</sup> p<0.01, \*\* p<0.05, \* p<0.1

**Logistic regression** 

| Logistic regression |        |         |          |               |        |           |     |
|---------------------|--------|---------|----------|---------------|--------|-----------|-----|
| anti2               | Coef.  | St.Err. | t-       | p-            | [95%   | Interval] | Sig |
|                     |        |         | value    | value         | Conf   |           |     |
| treatInfo           | -0.377 | 1.252   | -0.30    | 0.763         | -2.831 | 2.077     |     |
| Constant            | -3.178 | 0.726   | -4.38    | 0.000         | -4.601 | -1.755    | *** |
|                     |        |         |          |               |        |           |     |
| Mean dependent var  |        | 0.035   | SD depe  | endent var    |        | 0.185     |     |
| Pseudo r-squared    |        | 0.004   | Number   | of obs        | 86.000 |           |     |
| Chi-square          |        | 0.091   | Prob > c | chi2          |        | 0.763     |     |
| Akaike crit. (AIC)  |        | 29.933  | Bayesia  | n crit. (BIC) |        | 34.842    |     |
|                     |        |         |          |               |        |           |     |

<sup>\*\*\*</sup> p<0.01, \*\* p<0.05, \* p<0.1

| Coef. | St.Err. | t-  | p-  | [95%   | Interval]  | Sig   |
|-------|---------|---|---|--|--|---|
|       |         | value   | value   | Conf   |  |   |
| 0.067 | 0.475   | 0.14  | 0.887   | -0.863   | 0.998  |   |
| 0.754 | 0.305   | 2.47  | 0.013   | 0.156  | 1.351  | **  |
|       | 0.686   | SD dependent var 0.467                                |   |  |  |   |
|       | 0.000   | Number  | 1   |  |  |   |
|       | 0.020   | Prob > c  | hi2   |  | 0.887  |   |
|       | 111.003 | Bayesia   | n crit. (BIC)   |  | 115.912  |   |
|       | 0.067   | 0.067 0.475<br>0.754 0.305<br>0.686<br>0.000<br>0.020 | 0.067 0.475 0.14<br>0.754 0.305 2.47<br>0.686 SD depe<br>0.000 Number<br>0.020 Prob > c | value         value           0.067         0.475         0.14         0.887           0.754         0.305         2.47         0.013           0.686         SD dependent var           0.000         Number of obs           0.020         Prob > chi2 | value         value         Conf           0.067         0.475         0.14         0.887         -0.863           0.754         0.305         2.47         0.013         0.156           0.686         SD dependent var           0.000         Number of obs           0.020         Prob > chi2 | value         value         Conf           0.067         0.475         0.14         0.887         -0.863         0.998           0.754         0.305         2.47         0.013         0.156         1.351           0.686         SD dependent var         0.467           0.000         Number of obs         86.000           0.020         Prob > chi2         0.887 |

<sup>\*\*\*</sup> p<0.01, \*\* p<0.05, \* p<0.1

# 8. The rest of the models

**Logistic regression** 

| discussion         | Coef.  | St.Err. | t-       | p-            | [95%   | Interval] | Sig |
|--------------------|--------|---------|----------|---------------|--------|-----------|-----|
|                    |        |         | value    | value         | Conf   |           |     |
| treatAnger         | 0.064  | 0.276   | 0.23     | 0.816         | -0.476 | 0.604     |     |
| Constant           | -0.652 | 0.203   | -3.21    | 0.001         | -1.050 | -0.254    | *** |
| Mean dependent var |        | 0.350   | SD depe  | endent var    |        | 0.478     |     |
| Pseudo r-squared   |        | 0.000   | Number   | of obs        |        | 234.000   |     |
| Chi-square         |        | 0.054   | Prob > c | hi2           |        | 0.816     |     |
| Akaike crit. (AIC) |        | 307.075 | Bayesia  | n crit. (BIC) |        | 313.985   |     |

<sup>\*\*\*</sup> p<0.01, \*\* p<0.05, \* p<0.1

Logistic regression

| 394 0.279<br>338 0.212 | value<br>1.41<br>-3.95 | value<br>0.158<br>0.000     | -0.153                                   | 0.941                                    |   |
|------------------------|------------------------|-----------------------------|--|--|---|
|                        |                        |                             |  |  |   |
| 0.212                  | -3.95                  | 0.000                       | 1 254                                    | 0.400                                    |   |
|                        |                        | 0.000                       | -1.254                                   | -0.423                                   | ***   |
| 0.256                  | OD 1                   | 4                           |  | 0.450                                    |   |
| 0.350                  | SD dep                 | SD dependent var            |  | 0.478                                    |   |
| 0.007                  | Number                 | Number of obs               |  | 234.000                                  |   |
| 1.989                  | Prob >                 | Prob > chi2                 |  | 0.158                                    |   |
| 305.111                | Bayesia                | an crit. (BIC)              |  | 312.022                                  |   |
|                        | 0.007<br>1.989         | 0.007 Numbe<br>1.989 Prob > | 0.007 Number of obs<br>1.989 Prob > chi2 | 0.007 Number of obs<br>1.989 Prob > chi2 | 0.007       Number of obs       234.000         1.989       Prob > chi2       0.158 |

<sup>\*\*\*</sup> p<0.01, \*\* p<0.05, \* p<0.1

| discussion         | Coef.  | St.Err. | t-<br>value | p-<br>value   | [95%<br>Conf | Interval] | Sig |
|--------------------|--------|---------|-------------|---------------|--------------|-----------|-----|
| 0b.treatAnger      | 0.000  |         | varue       | varue         | Com          |           |     |
| 1.treatAnger       | 0.325  | 0.429   | 0.76        | 0.449         | -0.516       | 1.167     |     |
| 0b.treatInfo       | 0.000  |         |             |               |              |           |     |
| 1.treatInfo        | 0.641  | 0.419   | 1.53        | 0.126         | -0.180       | 1.463     |     |
|                    | 0.000  |         |             |               |              |           |     |
| 0b.treatAnger#0    |        |         |             |               |              |           |     |
| b.t~o              |        |         |             |               |              |           |     |
|                    | 0.000  | •       |             | •             |              |           |     |
| 0b.treatAnger#1    |        |         |             |               |              |           |     |
| o.t~o              |        |         |             |               |              |           |     |
|                    | 0.000  |         | •           |               | •            |           |     |
| 1o.treatAnger#0    |        |         |             |               |              |           |     |
| b.t~o              |        |         |             |               |              |           |     |
|                    | -0.451 | 0.563   | -0.80       | 0.423         | -1.555       | 0.652     |     |
| 1.treatAnger#1.t   |        |         |             |               |              |           |     |
| re~o               |        |         |             |               |              |           |     |
| Constant           | -1.019 | 0.324   | -3.14       | 0.002         | -1.654       | -0.383    | *** |
| Mean dependent var |        | 0.350   | SD depe     | endent var    |              | 0.478     |     |
| Pseudo r-squared   |        | 0.009   | Number      | of obs        |              | 234.000   |     |
| Chi-square         |        | 2.627   | Prob > c    | chi2          |              | 0.453     |     |
| Akaike crit. (AIC) |        | 308.410 | Bayesia     | n crit. (BIC) |              | 322.231   |     |
|                    |        |         |             |               |              |           |     |

\*\*\* p<0.01, \*\* p<0.05, \* p<0.1

Logistic regression

| immigration              | Coef. | St.Err. | t-            | p-            | [95%   | Interval] | Sig |
|--------------------------|-------|---------|---------------|---------------|--------|-----------|-----|
| -                        |       |         | value         | value         | Conf   |           |     |
| treatAnger               | 0.072 | 0.280   | 0.26          | 0.796         | -0.477 | 0.622     |     |
| Constant                 | 0.693 | 0.205   | 3.39          | 0.001         | 0.292  | 1.094     | *** |
| Mean dependent var 0.675 |       |         | SD depe       | endent var    |        | 0.469     |     |
| Pseudo r-squared         |       | 0.000   | Number of obs |               |        | 234.000   |     |
| Chi-square               |       | 0.067   | Prob > chi2   |               |        | 0.796     |     |
| Akaike crit. (AIC)       |       | 298.972 | Bayesia       | n crit. (BIC) |        | 305.883   |     |
|                          |       |         |               |               |        |           |     |

<sup>\*\*\*</sup> p<0.01, \*\* p<0.05, \* p<0.1

| immigration        | Coef.  | St.Err. | t-               | p-            | [95%   | Interval] | Sig |
|--------------------|--------|---------|------------------|---------------|--------|-----------|-----|
|                    |        |         | value            | value         | Conf   |           |     |
| treatInfo          | -0.596 | 0.288   | -2.07            | 0.039         | -1.161 | -0.031    | **  |
| Constant           | 1.074  | 0.223   | 4.81             | 0.000         | 0.636  | 1.511     | *** |
|                    |        |         |                  |               |        |           |     |
| Mean dependent var |        | 0.675   | SD dependent var |               |        | 0.469     |     |
| Pseudo r-squared   |        | 0.015   | Number of obs    |               |        | 234.000   |     |
| Chi-square         |        | 4.273   | Prob > chi2      |               |        | 0.039     |     |
| Akaike crit. (AIC) |        | 294.650 | Bayesia          | n crit. (BIC) |        | 301.560   |     |
|                    |        |         |                  |               |        |           |     |

<sup>\*\*\*</sup> p<0.01, \*\* p<0.05, \* p<0.1

| Coef.  | St.Err.   | t-  | <b>p-</b>     | [95%          | Interval]  | Sig  |
|--------|---|---|---------------|---------------|--|--|
|        |   | value   | value         | Conf          |  |  |
| 0.000  |   |   | •             | •             | •  |  |
| 0.503  | 0.450   | 1.12  | 0.263         | -0.379        | 1.385  |  |
| 0.000  | •   |   | •             | ·             |  |  |
| -0.225 | 0.413   | -0.55   | 0.586         | -1.035        | 0.585  |  |
| 0.000  | •   |   | •             | ·             |  |  |
|        |   |   |               |               |  |  |
|        |   |   |               |               |  |  |
| 0.000  |   |   |               |               |  |  |
|        |   |   |               |               |  |  |
|        |   |   |               |               |  |  |
| 0.000  |   |   |               |               |  |  |
|        |   |   |               |               |  |  |
|        |   |   |               |               |  |  |
| -0.715 | 0.581   | -1.23   | 0.218         | -1.853        | 0.423  |  |
|        |   |   |               |               |  |  |
|        |   |   |               |               |  |  |
| 0.818  | 0.311   | 2.63  | 0.008         | 0.209         | 1.427  | ***  |
|        | 0.675   | SD depe   | endent var    |               | 0.469  |  |
|        | 0.020   | _   |               |               | 234.000  |  |
|        | 5.625   |   |               |               | 0.131  |  |
|        | 297.048   |   |               |               | 310.869  |  |
|        | 0.000<br>0.503<br>0.000<br>-0.225<br>0.000<br>0.000<br>-0.715 | 0.000 . 0.503 0.450 0.0000.225 0.413 0.000 .  0.000 .  -0.715 0.581  0.818 0.311  0.675 0.020 5.625 | value   value | value   value | value         value         Conf           0.000         . | value         value         Conf           0.000 |

<sup>\*\*\*</sup> p<0.01, \*\* p<0.05, \* p<0.1

Logistic regression

| Dogistic regression |        |         |               |               |        |           |     |
|---------------------|--------|---------|---------------|---------------|--------|-----------|-----|
| willingness         | Coef.  | St.Err. | t-            | p-            | [95%   | Interval] | Sig |
|                     |        |         | value         | value         | Conf   |           |     |
| treatAnger          | -0.021 | 0.369   | -0.06         | 0.955         | -0.743 | 0.702     |     |
| Constant            | 1.749  | 0.271   | 6.44          | 0.000         | 1.217  | 2.281     | *** |
| Mean dependent var  |        | 0.850   | SD depe       | endent var    |        | 0.357     |     |
| Pseudo r-squared    |        | 0.000   | Number of obs |               |        | 234.000   |     |
| Chi-square          |        | 0.003   | Prob > chi2   |               |        | 0.955     |     |
| Akaike crit. (AIC)  |        | 201.477 | Bayesia       | n crit. (BIC) |        | 208.388   |     |
|                     |        |         |               |               |        |           |     |

<sup>\*\*\*</sup> p<0.01, \*\* p<0.05, \* p<0.1

| Coef.                                  | St.Err. | t-  | p-            | [95%                | Interval]                | Sig   |
|--|---------|---|---------------|---------------------|--------------------------|---|
|  |         | value   | value         | Conf                |                          |   |
| -0.846                                 | 0.401   | -2.11   | 0.035         | -1.632              | -0.060                   | **  |
| 2.262                                  | 0.333   | 6.79  | 0.000         | 1.609               | 2.914                    | ***   |
|  | 0.850   | SD depe                                       | endent var    |                     | 0.357                    |   |
|  | 0.024   | Number  | of obs        |                     | 234.000                  |   |
|  | 4.450   | Prob > c                                      | hi2           |                     | 0.035                    |   |
| Chi-square 4<br>Akaike crit. (AIC) 196 |         | Bayesia                                       | n crit. (BIC) |                     | 203.575                  |   |
|  | -0.846  | -0.846 0.401<br>2.262 0.333<br>0.850<br>0.024 | value  -0.846 | value value  -0.846 | value value Conf  -0.846 | value         value         Conf           -0.846         0.401         -2.11         0.035         -1.632         -0.060           2.262         0.333         6.79         0.000         1.609         2.914           0.850         SD dependent var 0.357         0.024         Number of obs 234.000         234.000           4.450         Prob > chi2         0.035 |

<sup>\*\*\*</sup> p<0.01, \*\* p<0.05, \* p<0.1

| willingness        | Coef.  | St.Err. | t-       | p-            | [95%   | Interval] | Sig |
|--------------------|--------|---------|----------|---------------|--------|-----------|-----|
|                    |        |         | value    | value         | Conf   |           |     |
| 0b.treatAnger      | 0.000  | •       |          | •             |        | •         | _   |
| 1.treatAnger       | -0.280 | 0.679   | -0.41    | 0.680         | -1.610 | 1.050     |     |
| 0b.treatInfo       | 0.000  | ·       |          |               |        | •         |     |
| 1.treatInfo        | -1.055 | 0.615   | -1.72    | 0.086         | -2.261 | 0.151     | *   |
|                    | 0.000  |         |          | •             | •      |           |     |
| 0b.treatAnger#0    |        |         |          |               |        |           |     |
| b.t~o              |        |         |          |               |        |           |     |
|                    | 0.000  |         |          | •             | •      |           |     |
| 0b.treatAnger#1    |        |         |          |               |        |           |     |
| o.t~o              |        |         |          |               |        |           |     |
|                    | 0.000  |         | •        |               |        | •         |     |
| 1o.treatAnger#0    |        |         |          |               |        |           |     |
| b.t∼o              |        |         |          |               |        |           |     |
|                    | 0.375  | 0.813   | 0.46     | 0.644         | -1.218 | 1.969     |     |
| 1.treatAnger#1.t   |        |         |          |               |        |           |     |
| re~o               |        |         |          |               |        |           |     |
| Constant           | 2.420  | 0.523   | 4.63     | 0.000         | 1.396  | 3.445     | *** |
|                    |        |         |          | 4/ 4          |        |           |     |
| Mean dependent var |        | 0.850   |          | endent var    |        | 0.357     |     |
| Pseudo r-squared   |        | 0.025   | Number   |               |        | 234.000   |     |
| Chi-square         |        | 4.585   | Prob > c |               |        | 0.205     |     |
| Akaike crit. (AIC) |        | 200.445 | Bayesia  | n crit. (BIC) |        | 214.267   |     |
|                    |        |         |          |               |        |           |     |

<sup>\*\*\*</sup> p<0.01, \*\* p<0.05, \* p<0.1

# **Chapter 5—Conclusion**

## I. Misinformation and Democracy

The citizens of an ideal democracy should be well-informed about politics. They ought to know its values, the way their government works, and which politicians they should elect. This is, however, rarely the case in reality. Democratic theory tells us that voters do not have sufficiently strong incentives to learn (Downs, 1957), and that humans navigate using shortcuts and can make decisions based on low levels of information (Popkin, 1994; Lupia and McCubbins, 1998; Tversky and Kahneman, 1986).

Things may, however, be changing. Voters do not need strong incentives to learn about politics todays. Information comes to them cheaply and easily, on a device that they carry everywhere with them. More importantly, they receive most of this information from social media sites where they are in a social environment; political learning has, in some cases, become a social activity. By reading a news article or tweets and sharing it on social media, individuals may get attention from their followers. In other words, consuming political information has for many become a daily activity with social consequences.

The main problem associated with this development is the volume of false or misleading information that individuals encounter in this process. Several scholars have documented the existence of false news and other types of inaccurate information on social media sites. Given the lack of gatekeeping and other verification mechanisms, false news, conspiracy theories or other unverified rumors can reach millions of people in a short period.

#### III. MAIN FINDINGS AND SHORTCOMINGS

In this multi-paper dissertation, my goal was to provide an in-depth understanding of the dissemination of mis-, disinformation on social media and its political implications. The findings show us that social media usage is associated with being misinformed. Furthermore, echo-chambers are emotional spaces, particularly during influential events. Finally, I find that imagined echo-chambers increase the willingness to share false news articles. However, when participants are assigned to real chat environments, being told about the attitudes of the chat group members reduces the sharing of false information. A more detailed discussion of the results follows below.

## A. The Political Implications of Social Media Usage

The second chapter tells us a nuanced story. In this chapter, I analyzed nationally representative survey data collected in Turkey in 2015. Turkey provides a valuable case to examine due to the high levels of social media usage and the fact that it is an underrepresented case in the literature.

I first examine the relationship between internet and social media usage and different components of political knowledge: being informed, misinformed, or uninformed. I do this by conducting OLS regressions and show that using the internet is associated with being more informed. This result does not hold for social media usage, however, as those who more frequently use social media are more likely to be misinformed and less likely to be uninformed. This result may be due to polarization among those who use social media. They may be more confident about what they think they know while being misinformed. This is worrisome as those who use social media

may think they are getting informed about politics but may instead be consuming lowquality information.

#### B. What do People Share on Social Media?

In the third chapter, I presented a detailed qualitative and descriptive analysis of two echo-chambers on Twitter. Given the lack of qualitative studies of echo-chambers, my goal was to observe the behavior of individuals who participate in echo-chambers during a political campaign. I collected the data for this research using covert participant observation. I opened two accounts and created two echo-chambers—one that is pro-government and one that is anti-government in Turkey. The qualitative part of the research was conducted when Turkey was preparing for a constitutional referendum in 2017. I observed the feeds that I created—composed of 406 accounts in total—on a daily basis during the month leading up to the vote in April 2017 and documented my findings through screenshots and notes. I continued to observe these accounts until June 2019 and conducted computational analyses of texts, social networks, and sentiments.

The findings of this chapter are multi-faceted. First of all, and perhaps unsurprisingly, false information comes in many shapes and sizes: false news, rumors, conspiracy theories, and half-truths. Many users share unverified rumors about the failings of the other side. These rumors are stronger if politicians or pundits led them rather than ordinary individuals. For example, as was the case in the night of the local elections in Istanbul, the rumors started by AKP officials were picked up by progovernment users, and consequently, several unverified rumors about election fraud were disseminated widely. What is even more concerning is that when this happens, fringe partisan news sites can build stories on them and increase their legitimacy.

People who participate in partisan echo-chambers, therefore, are not only exposed to unverified rumors but also news stories that back up them. Both echo-chambers had partisan fringe sites from which they shared misleading content to support their arguments. This further deteriorates the division between the members of two echo-chambers as they become even less perceptive of why the other side is acting in a certain way.

Another worrying trend was the tendency to promote conspiracy theories in both echo-chambers. Users in the pro-government echo-chamber were interpreting every political incident from a conspiratorial perspective. For example, they kept repeating the notion that the "No" campaign was cooperating with the Western countries to divide Turkey. Similarly, the "No" echo-chamber was arguing that the ultimate goal of the "Yes" campaign was to divide Turkey and found a federal state. Both echo-chambers had misconceptions about the West in general, and they interpreted irrelevant political events from a conspiratorial perspective.

Furthermore, both echo-chambers shared emotional material. This finding is in line with previous literature which suggests that emotionally charged content is more widely shared (see Stieglitz and Dan Xuan, 2013, for instance). The participants of the echo-chambers have an audience, and they get more attention when the language and the images that they share are intense and emotional. This is a risky trend, especially when a significant event happens.

The polarized nature of echo-chambers and the emotional state of the participants facilitate the dissemination of inaccurate content. In both echo-chambers, the participants frequently got angry, afraid, or enthusiastic, and during these times, they were more inclined to share less cautiously. As I provided sentiment analyses of emojis from several hashtags, sentimentality score varies over time and according to

the nature of the hashtag. While some issues create enthusiasm—making fun of the other side—others may evoke nationalist feelings.

Overall, while this chapter provides a detailed and descriptive explanation of echo-chambers, the results are limited to the two echo-chambers that I created superficially. The two echo-chambers I created were hyper-partisan and may, therefore, not represent the whole universe of echo-chambers. Many people who do not have strong partisan attachments may follow outlets and individuals who are politically different from themselves. It may be worthwhile to consider the growing literature arguing against the prevalence of echo-chambers on social media (See Barbera et al., 2015, for instance).

Furthermore, the two echo-chambers that I observed were very active during my observations, mainly because of the election campaign. During less polarized periods, they may behave differently. They may be less emotional as well as more cautious about what they read and share. I carried out the computational analyses later on to eliminate this problem, but Turkey had a general election in 2018 and a local election in 2019. The continuous election campaigns did not allow me to have sufficient non-election observations from these echo-chambers.

Finally, the observations could be limited to the case selected, which is Turkey. It may be an excellent addition to expand this type of qualitative research to other countries that also have high levels of social media usage.

## C. Why do People Share False Information?

As the findings in the previous chapter suggest that emotional users in echo-chambers share significant amounts of false content, I designed two experiments to test whether this is actually the case. Many users in the two echo-chambers I followed were

occasionally angry, which is why I focused on this emotion. I also wanted to test the idea that echo-chambers facilitate the dissemination of false information (Törnberg, 2018). To do this, I conducted two lab experiments—one in Turkey in 2018 and the other in the United Kingdom in 2019.

In the first experiment, I induced anger through 'autobiographical recall' among randomly selected participants. Next, all the participants read a fabricated news article. They were then instructed to imagine a social media group composed of participants who were 18-25 years old. Participants were also randomly told that the group supported the AK Party, CHP or were not told anything about the party affiliation. The main outcome of interest was the participants stated willingness to share the news article.

In the second experiment, randomly selected participants were first told to write about personal and a political memory that made them angry. Next, they were randomly assigned to read a misleading (positive or negative) news article about immigration. Finally, they were randomly assigned to chat groups before which they either received or did not receive information regarding the attitudes of the other participant in the chat group. The primary outcome of interest in this experiment is whether or not the subjects shared specific information about the articles in the chat groups.

In both experiments, anger did not cause any statistically significant effects, which may be due to a failure to induce anger among the treatment group members rather than anger as such not having an effect. In both experiments, there is no difference between the anger treatment and control groups in terms of the level of anger they felt after the treatment. Anger may affect sharing behavior, but I may have been unable to capture it in my samples most probably because the method of induction did not work well.

Second, the echo-chamber treatments had mixed results. In the pilot experiment I conducted in Turkey, the outcome variable was the willingness to share a false news article. In this experiment, those who were asked to imagine a like-minded social media group were more willing to share the article than those who were not told about the group's political affiliation.

However, in the second experiment, participants who received information about the attitudes of the other participant in a real chat environment were less likely to share false information. A sub-group analysis showed that the cross-cutting chat groups mainly drove this effect, where the participants were assigned to talk to participants who did not have similar attitudes on immigration. The participants in these groups were less willing to talk about immigration and chat with the other participants.

The findings of this research are noteworthy for several reasons. First, the inability to induce anger among the subjects is significant. Was this failure mainly due to the treatment method? If that is the case, we may need to find alternative ways of inducing anger in political psychology research.

Second, while I found a positive effect of echo-chambers on the willingness to share false news articles, this experiment does not measure the actual sharing behavior. Asking participants to imagine a group of people may not capture the real essence of echo-chambers. However, it may still give us an idea about how imagined echo-chambers may affect the way people decide what to share. For example, more partisan people may decide to share impulsively when they perceive their audience to have similar political attitudes. They may be less cautious about the quality of the information they are sharing because they are among similar people, who would not embarrass them in case of a mistake.

In the second experiment, I changed the outcome to measure the actual sharing of false information, which strengthens the research. The chat group allows us to observe how the participants behave in a real-life setting when they know about the attitude of the other participant. My initial expectation was that those who were told that they were in like-minded groups would feel that they were in a safer, less critical environment. While the net effect of being told the identity of the other chat participant reduced sharing, being told that you were in a like-minded group may still lead to an increase in sharing. I was, however, not able to detect such an effect (the effect of revealing the identity among those that were placed in like-minded groups was statistically insignificant).

There are also differences in terms of the way the experiments were conducted. The pilot experiment, for instance, has several shortcomings. First, the pilot study is done with a smaller sample. Furthermore, the students who participated in the experiment were not paid for their participation but were given course credit. To fix these issues, I increased the number of subjects and paid them for their time in the second experiment.

### II. Future Research

Misinformation is a complex phenomenon. There are countless shapes false information can take, which makes classification difficult. The reception of false information is also problematic to measure. Who chooses to consume false information, and why?

Furthermore, we do not know enough about the effects of consuming false information. For example, which types of false information do people believe the most?

How do they behave when they are exposed to false information in comparison to when they consume high-quality, correct information?

Although I tried to provide some answers to these questions in this dissertation, there is a lot to research yet to be done. Below are some ideas for future research on the research questions that I covered in this dissertation.

#### A. The Effects of False Information Online

We are well aware of the existence of online falsehoods, but what are some of the political effects? I found that social media usage is associated with being misinformed. One way to complement this survey research is to expand the items to measure the effects of self-reported exposure to falsehoods on social media. This would allow us to define the relationship between exposure to false news, rumors, conspiracy theories on social media, and being misinformed. Furthermore, it would be a significant improvement if we could collect panel data to evaluate the changes in social media usage and political knowledge over time.

Secondly, to understand how misleading or false content affects political knowledge, it is essential to understand what kind of information people choose to consume in an information environment where there are countless choices. This type of research could be done in a lab or online setting or through a field experiment.

Finally, better consistency in political knowledge measurement would help us conduct comparative research on the implications of social media usage on being misinformed, informed, and uninformed. International academic collaborations could achieve this among those who study political knowledge and media effects in various contexts.

#### **B.** Emotions

The failure to induce anger in both experiments is noteworthy. This result may be due to several reasons that future studies can improve. First, given that political scientists are not able to use many induction methods that clinical psychologists use, we may need to find the new ways of inducing emotions designed explicitly for political research. A comprehensive review of emotional induction methods in political psychology research could be a good starting point. Additionally, testing some induction methods in a lab or focus group setting to which one produces better results could also advance our understanding of the effects of emotions on political outcomes.

Finally, in both experiments, I used student samples. As they are young people, student subjects may not have memories strong enough to make them angry in a lab setting. Testing the lab experiment with an online sample composed of different age groups could allow me to compare the differences between the two types of samples.

# C. Sharing Behavior

Understanding the determinants of sharing behavior is critical for finding policy solutions to the mis- and disinformation problem. The first question is: do people share what they perceive to be correct? If so, what factors affect their judgment in deciding what content is correct or false?

These questions could be tested through lab or field experiments. For instance, eye-tracking could help us understand the type of content to which people pay the most attention. Next, we could measure the relationship between attention and perception of the content.

Further, a study that employs web-tracking could provide us a better understanding of sharing behavior in real social media settings. This type of research could be conducted as descriptive or experimental.

Finally, to understand the effect of emotions on the consumption and sharing of falsehoods, a field experiment could be conducted. Certain emotions could be induced at different times of the day among randomly selected participants to see if they have any effect on the consumption and sharing of information.

### D. Altering the Consumption and Sharing of Online Falsehoods

Mis- and disinformation has policy implications. Therefore, it is essential to come up with potential solutions. I would like to pursue this line of research by testing behavioral interventions such as nudges on consumption and sharing behavior. I am interested in testing the effect of gentle reminders or warnings to make people think more analytically and less emotionally about the political information they consume and share. This research could be done in many ways, including the use of social norms. In a social environment where individuals receive various types of information, ranging from high to low quality, reminding them of a better way to choose information could reduce the consumption and sharing of dubious content.

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