

PARTISAN SELECTIVE NEWS EXPOSURE AND POLITICAL  
POLARIZATION ON TWITTER NETWORKS IN TURKEY

A THESIS SUBMITTED TO  
THE GRADUATE SCHOOL OF SOCIAL SCIENCES  
OF  
MIDDLE EAST TECHNICAL UNIVERSITY

BY

SEYİT GÖLCÜK

IN PARTIAL FULFILLMENT OF THE REQUIREMENTS  
FOR  
THE DEGREE OF MASTER OF SCIENCE  
IN  
THE DEPARTMENT OF POLITICAL SCIENCE AND PUBLIC  
ADMINISTRATION

JUNE 2018



Approval of the Graduate School of Social Sciences

---

Prof. Dr. Tülin Gençöz  
Director

I certify that this thesis satisfies all the requirements as a thesis for the degree of Master of Science.

---

Prof. Dr. Ayşe Ayata  
Head of Department

This is to certify that we have read this thesis and that in our opinion it is fully adequate, in scope and quality, as a thesis for the degree of Master of Science.

---

Assoc. Prof. Dr. Nilay Yavuz  
Supervisor

**Examining Committee Members**

Assist. Prof. Özgür Avcı (METU, PADM) \_\_\_\_\_

Assoc. Prof. Dr. Nilay Yavuz (METU, PADM) \_\_\_\_\_

Prof. Dr. Emre Toros (Atılım Uni., SBKY) \_\_\_\_\_



**I hereby declare that all information in this document has been obtained and presented in accordance with academic rules and ethical conduct. I also declare that, as required by these rules and conduct, I have fully cited and referenced all material and results that are not original to this work.**

**Name, Last name:** Seyit Gölcük

**Signature** :

## **ABSTRACT**

### **PARTISAN SELECTIVE NEWS EXPOSURE AND POLITICAL POLARIZATION ON TWITTER NETWORKS IN TURKEY**

Gölcük, Seyit

M.S., Department of Political Science and Public Administration

Supervisor: Assoc. Prof. Dr. Nilay Yavuz

June 2018, 196 pages

This thesis aims to investigate the degree of partisan selective exposure, political polarization and their statistical association by using a Twitter data derived from Turkish political Twitter networks. Analysis of a sample of 2.790.339 unique users who have a total of 48.316.548 following links to political news outlets and political entities on Twitter reveals that, Turkish Twitter audiences identified with a political party exercise very high levels of partisan selective exposure to like-minded news outlets and very low levels of cross-cutting exposure to politically discrepant outlets. In addition, they are found to be very polarized in terms of disproportionately following pro-party deputies and retweeting accounts that share their own political views. The regression analyses with interaction terms supported the main hypothesis of this study in that, irrespective of the political party that is being favored of, partisanship combined with higher levels of like-minded news exposure is significantly associated with political polarization, whereas more cross-cutting exposure among partisans is related with less

polarized attitudes. Moreover, validation of the partisanship and polarization measures strengthens the findings of this study.

**Keywords:** Partisan selective exposure, cross-cutting news exposure, political polarization, social network analysis, Twitter.

## ÖZ

### TÜRKİYE'DE TWİTTER BAĞLAMINDA KENDİ SİYASİ GÖRÜŞÜNE YAKIN HABERLERİ TAKİP ETME VE SİYASAL KUTUPLAŞMA İLİŞKİSİ

Gölcük, Seyit

Yüksek Lisans, Siyaset Bilimi ve Kamu Yönetimi Bölümü

Tez Yöneticisi: Doç. Dr. Nilay Yavuz

Haziran 2018, 196 sayfa

Bu tez, Twitter'dan elde edilen özgün bir veriseti kullanılarak, kendi siyasi görüşüne yakın haberlere maruz kalma, siyasi kutuplaşma ve bu ikisi arasındaki istatistiksel ilişkiyi araştırmayı hedeflemektedir. Twitter'dan çekilen 2.790.339 kişilik bir örneklem ve bu kişiler arasındaki toplam 48.316.548 farklı siyasi haber ve milletvekili hesaplarını takip etme ilişkisi analiz edildiğinde, bir partiye yakınlık duyan Türk Twitter kullanıcılarının kendi siyasi görüşlerine yakın haber sitelerini yüksek derecede takip ettikleri, fakat kendi görüşlerine zıt fikirler içeren haber sitelerine ait hesapları çok az derecede takip ettikleri ortaya çıkmaktadır. Dahası, bu kullanıcıların, orantısız bir şekilde kendi görüşlerini temsil eden milletvekillerini takip etme ve yine orantısız bir şekilde kendi görüşlerine yakın popüler hesapları retweet etme bağlamında oldukça kutuplaştıkları görülmektedir. Yapılan regresyon analizleri, çalışmanın ana hipotezi olan, yakınlık hissedilen parti hangisi olursa olsun, bir partiye yakınlık ve aynı



görüŖte haberlere maruz kalmanın etkileŖme girerek kutuplaŖmaya yol açtıđı, diđer yandan zıt görüŖlü haberlere maruz kalmanın ise bu partililerin kutuplaŖmıŖ tutumlarını azalttıđı hipotezini desteklemektedir. Tezin bulguları, olası sonuçları ve ileriye dönük çalıŖma önerileri ayrıca tezde tartıŖılmıŖtır.

**Anahtar Kelimeler:** Aynı görüŖte habere maruz kalma, karŖıt siyasi görüŖten haberlere maruz kalma, siyasal kutuplaŖma, sosyal network analizi, Twitter.

## ACKNOWLEDGMENTS

First and foremost, I would like to express my gratitude to my supervisor Assoc. Prof. Dr. Nilay Yavuz, as she always believed in me, supported my studies and motivated my enthusiasm for my academic progress. It is a great honor for me to have an advisor like her, who encourages her students to delve into researches even on new and challenging fields.

I am also grateful to my wife Merve, who always encouraged me in the academic field and sincerely supported me during my thesis writing.

I would also like to express my sincere thanks to my friend Fatih, who helped me with the statistical design of this thesis. Without his support, this thesis might not have been completed.

Last but not the least, I would like to thank to my 3-year-old son, whose existence has always been a source of inspiration for my studies.

## TABLE OF CONTENTS

PLAGIARISM.....	iii
ABSTRACT .....	iv
ÖZ.....	vi
ACKNOWLEDGMENTS.....	viii
TABLE OF CONTENTS .....	ix
LIST OF TABLES.....	xiii
LIST OF FIGURES.....	xiv
CHAPTER	
1. INTRODUCTION .....	1
2. INVESTIGATING SELECTIVE EXPOSURE PHENOMENON.....	7
2.1 Partisan Selective Exposure to Congenial Media Sources .....	12
2.2 Partisan Selective Exposure to Online Media Sources .....	16
2.2.1. Twitter as a Medium for Attracting Partisan Selective Exposure .....	21
2.3 Predictors of Partisan Selective Exposure .....	23
2.3.1 Political Interest .....	23
2.3.2 News use frequency .....	24
2.3.3 Political engagement and participation .....	24
2.3.4 Political Knowledge .....	25

2.3.5	Strength of Partisanship / Ideology.....	26
2.3.6	Media Fragmentation.....	27
2.4	Potential Effects of Selective Exposure for Democracy and Politics.....	30
3.	POLITICAL POLARIZATION.....	37
3.1	Dimensions of Political Polarization .....	38
3.2	Indicators of Political Polarization.....	40
3.2.1	Partisan Polarization .....	41
3.2.2	Ideological Polarization .....	42
3.2.3	Issue-Based Polarization.....	45
3.2.4	Affective Polarization.....	47
3.3	Effects of Selective Exposure on Political Polarization.....	50
3.4	Hypotheses of This Study .....	57
4.	METHODOLOGY.....	60
4.1	Partisan Selective Exposure on Twitter.....	60
4.1.1	Conceptual Framework for the Selective Exposure Methodology .....	60
4.1.2	Data.....	65
4.1.3	Measurement.....	69
4.1.3.1	Measuring News Outlets' Partisan Leanings .....	69
4.1.3.1.1	Operationalization (Political Proximity and Clustering of News Outlets).....	74

4.1.3.2 Measuring Twitter Users' Partisan Leanings .....	90
4.1.3.2.1 Operationalization (Political Predispositions of Twitter Users).....	92
4.1.3.3 Measuring Partisan Selective Exposure on Twitter.....	98
4.1.3.3.1 Operationalization (Partisan Selective Exposure).....	90
4.1.3.2 Measuring Twitter Users' Partisan Leanings .....	90
4.2 Measuring Partisan Polarization on Twitter .....	101
4.3 The Association Between Partisan Selective Exposure and Polarization .....	102
4.3.1 Variables .....	103
4.3.2 Measurement of the Variables.....	106
4.4 Validation of the Polarization and Partisanship Measures.....	107
4.4.1 Alternative Measurement of Polarization.....	107
4.4.2 Alternative Measurement of Partisanship .....	109
5. ANALYSES AND RESULTS .....	111
5.1 Partisanship and Selective Exposure.....	111
5.2 Polarization .....	120
5.3 Partisan Selective Exposure and Polarization.....	124
5.4 Assessing the Validity of Polarization and Partisanship Measures.....	128
6. DISCUSSION AND CONCLUSION.....	133

REFERENCES.....	149
APPENDICES	
A. WHOLE LIST OF TWITTER ACCOUNTS THAT ARE RETWEETED BY THE SAMPLE TWITTER AUDIENCE .....	166
B. LIST OF POLITICAL KEYWORDS USED TO CREATE “POLITICAL INTEREST” VARIABLE.....	171
C. POLITICALLY CONTROVERSIAL HASHTAGS FOR “POLITICAL DISCUSSION” VARIABLE .....	173
D. TURKISH SUMMARY / TÜRKÇE ÖZET .....	178
E. TEZ FOTOKOPİSİ İZİN FORMU .....	196

## LIST OF TABLES

Table 1 Descriptive Information about Turkish Political News Outlets on Twitter.....	66
Table 2 Formula of Chi-Square Measure for 2*2 Contingency Tables .....	77
Table 3 Computing Chi-square Similarity between Gazete2023 - Etikhaber and Gazete203-Hurriyet Newspapers .....	78
Table 4 Clustering Positions of 53 Outlets in Selective Exposure (S.E.) and Partisan S.E Networks with Different Resolutions .....	84
Table 5 Z-Score Distribution of Party Deputies Based on their Followers on Twitter.....	93
Table 6 Strength of Party Identifications Illustrated as Three-Quartiles ....	96
Table 7 Party Identification Strength Illustrated as Quartiles for each Political Party Supporters.....	97
Table 8 Selective News Exposure to Pro-party News Outlets.....	112
Table 9 Partisan Selective Exposure and Odds Ratios of Pro-party Twitter Users.....	115
Table 10 Polarization Indices Based on Political and Retweet Polarization on Twitter .....	121
Table 11 Regression Analysis Predicting Political Polarization.....	124
Table 12 Regression Analyses Predicting Retweet Polarization .....	129
Table 13 Comparison of the Partisanship Measurements .....	131

## LIST OF FIGURES

Figure1 Illustration of the Logic Behind the Partisan Selective Exposure Network.....	81
Figure 2 Illustration of Transformed Relationship between News Outlets and Political Parties Based on their Co-followers .....	82
Figure 3 Partisan Clustering of News Outlets .....	90
Figure 4 Retweet Polarization of Pro-party and Politically Mixed Twitter Users .....	122
Figure 5 Interaction between Pro-AKP News Exposure and Partisanship on Polarization .....	127
Figure 6 Interaction between Pro-CHP News Exposure and Partisanship on Polarization .....	127
Figure 7 Interaction between Pro-HDP News Exposure and Partisanship on Polarization .....	128
Figure 8 Interaction between Pro-MHP News Exposure and Partisanship on Polarization .....	128



## CHAPTER 1

### INTRODUCTION

What motivates people to support a political party or a candidate. What are the channels through which this motivation strengthens or weakens? For decades, scientists are seeking out answers to these questions. Basically, the theories are built on two different perspectives which reflect different aspects of two prominent American schools. The Colombian school, pioneered by Paul Lazarsfeld and his colleagues, focuses on social-interactive perspective and argues that voting choice and political orientation is highly influenced by social structure. The researchers in this school emphasize the impact of interpersonal communications among the members of the same community; family, neighbors, friends, and colleagues, in which an individual is embedded (Berelson, Lazarsfeld, & McPhee, 1954; Katz & Lazarsfeld, 1955; Lazarsfeld, Berelson, & Gaudet, 1944). In his book, *The People's Choice*, Lazarsfeld (1944) notes that people's political attitudes are shaped by and strongly related to their social environments. Colombian sociologists focus on group processes by examining how and through what channels an information reaches to the voters, rather than what information eventually reaches to them (Sheingold 1973). Moreover, their findings suggest that the type or amount of media content voters are exposed has little importance in influencing their decision (e.g., Berelson et al., 1954). Instead, it is the socially homogeneous communities (based on religion, political orientation, social class, income rate etc.) and the face-to-face communication with like-minded people in these communities that shapes and reinforces a voter's political behavior.

Their famous theory, *two-step flow of information*, argues that opinion leaders in a homogeneous network is politically much more influential than the other sources of information such as mass media (Katz & Lazarsfeld, 1955; Lazarsfeld et al., 1944)

The other school, on the other hand, consists of the researchers in the Michigan University's Survey Research Center (SRC), who conducted national surveys in U.S. in 1950s. These surveys were aiming to measure the political behavior of the American voter by mainly focusing on their aggregate level psychological and attitudinal perspectives (Campbell & Cooper, 1956; Campbell, Gurin, & Miller, 1954; Campbell & Kahn, 1952; Campbell & Miller, 1957). They primarily concentrated on cognitive, affective and evaluative factors of voters to understand their political behavior (Eulau & Siegel, 1981). Their prominent study, *The American Voter* (Campbell, Converse, Miller, & Stokes, 1960) argues that voting behavior is largely shaped by political attitudes (party identification, loyalty, group membership, perception on the political issues, political content, and candidates) and their short and long term effects on voting behavior.

Michigan model is much criticized by the scholars of structural perspective, especially for its assumption that opinions are formed in a social vacuum rather than a social network (Morales, Borondo, Losada, & Benito, 2015) and for separating the voters from their social contexts and relationships which have the high potential to affect their attitudes (Knoke, 1990). On the other side, the Columbian model is also criticized by Michigan school for removing politics out of the voting studies and just concentrating on the social contexts (Key & Munger, 1959).

For both schools, selective exposure, *which means choosing to consume like-minded political information while avoiding from challenging opinions*, occupies an important position in understanding political behavior. From socio-structural perspective, selective exposure to like-minded information in politically homogeneous networks has great impact on shaping and reinforcing political orientations. According to this perspective, availability of information combined with political predispositions determine selective exposure (Lazarsfeld et al., 1944). From attitudinal perspective, selective exposure to like-minded information is a key factor to strengthen one's existing attitudes and counter-attitudinal exposure is a key indicator of cognitive dissonance (Festinger, 1962). Whether being exposed to homogeneous interpersonal networks or homogeneous media sources, many scholars warn about the possible consequences of selective exposure to politically congenial information, and selective avoidance to uncongenial information as well. The main fear behind this one-sided media exposure is attitude polarization, which means reinforcement of political attitudes toward the direction that is previously being inclined, and which falls apart the society into mutually opponent clusters. Cass Sunstein suggests that fragmentation on society based on diverse communication and media consumption habits have a strong potential to breed attitude extremism, polarization, and even violence and hatred. He also suggests that selective exposure to like-minded news and selective avoidance from contradictory views lead audience, who are not originally fixed in their political opinions, and not so fragmented, to move toward extremely separate positions, just because of what they consume in their news diets (Sunstein, 2007).

Although there is not an academic study in Turkey that directly focus on partisan selective news exposure, political polarization and their

relationship, past studies on Turkish political science imply a high level of like-minded news consumption and political polarization. For example, Kiriş (2012) highlights the effect of ideological and identity-based polarization in Turkish political system. He argues that party elite's polarized attitudes in Turkey enable to create their own loyal electorates by sharpening their moderate attitudes and by making them develop highly partisan party identifications (Kiriş, 2012). On the other hand, Çarkoğlu and his colleagues point to a high level of media fragmentation and press-party parallelism in Turkey. Moreover, Sayarı (2007) argues that this press-party parallelism and non-democratic interactions between political elites and media owners are related with a polarized political party system in Turkey. Similarly, Erişen (2013) suggests that Turkish political system's structure creates high level of partisan attachment and party identification among the electorates, which prevent them to be affected from the diverse and oppositional views that are expressed within their social networks.

Both partisan selective news exposure and polarization have negative effects for communities. As Habermas notes, to be able to evaluate both sides of a controversial issue, people should be exposed to cross-cutting views, which is also vital for encouraging political dialog and democratic citizenry (Habermas, 1989). Otherwise, exposing only to pro-attitudinal information would do no more than reinforcing pre-existing attitudes, and accordingly increasing polarization on a society. On the other hand, if not helps to change one's existing ideas, exposing to diverse opinions would at least give people opportunity to make empathy for contrasting ideas and to see their already-possessed position through the window of oppositional views (Mill, 1859).

When considering Turkey's political history including social conflicts, military interventions, coups, economic crises and non-democratic practices, the importance of understanding the level of polarization and its relationship with media selectivity becomes more clearer. In order to understand the ongoing political polarization among both political elites and the mass Turkish society, and in order to decrease its great damage to the Turkey's democratic development, this problem should be investigated with a broader point of view.

Therefore, this study aims to take a recent picture of the level of partisan selective news exposure and political polarization in Turkey by using an original Twitter data. Moreover, it aims to investigate the degree of association between consuming like-minded political news on Twitter and having polarized attitudes toward the own party.

Few of us believe that we are all polarized, and many others accuse others (and other party supporters) to have polarized attitudes. Similarly, most of us think that we consume political views from all sides of the political spectrum while our opponents are not like us and they are mostly slanted toward like-minded information. One of the main efforts in this study is to reveal whether this polarization and slanted media consumption is peculiar to just a political group or to the whole electorate. On the other hand, the most important research question of this thesis is whether these two phenomena, *partisan selective news exposure and polarization*, have a significant association. Although past research abroad finds a significant association between these two, it is yet not tested in Turkish political system, which might be quite different compared to the western democracies.

If indeed these two phenomena are real and related with each other in the Turkish political context, this would mean a lot for each one of us. Knowing that consuming only like-minded political information is related with polarization would bring along with it the solutions. Partisan media's role in polarizing attitudes would have some implications for decision makers from political and media sector. At least, the findings would offer cross-cutting news exposure as an origin to decrease the level of political polarization. Moreover, the findings would make all of us to review ourselves, our polarized attitudes and our slanted media consumption habits.

## CHAPTER 2

### INVESTIGATING SELECTIVE EXPOSURE PHENOMENON

In political communication literature, “selective exposure” has been of interest for a long time. People seek out information which are reinforcing or consistent with their previous beliefs, and they avoid seeking out information which challenges their existing beliefs (Klapper, 1960). Therefore, selective exposure phenomenon refers to the selection of information which aligns with the pre-existing points of view. This information selection might be exercised on various contexts; including politics, ideologies, ethnicity, sub-culture and gender.

Selective exposure thesis hinges upon Festinger’s (1962) cognitive dissonance theory. According to this theory, information that is consistent with the pre-existing attitudes generate positive feelings. On the other hand, information that is inconsistent with the pre-existing attitudes generate psychological discomfort and uneasiness. Festinger (1962) argues that people’s views and attitudes are tended to remain in internally-consistent clusters. By choosing the term “dissonance” in the place of “inconsistency”, he argues that a dissonance between an opinion/attitude and the person’s cognition/behavior will motivate that person to decrease the level of dissonance, and thus to reach consonance. In line with the topic of this thesis, being exposed to an information in a news outlet that is contradictory to an audience’s political views would arouse dissonance. For example, reading a news article supporting the views of the ruling AKP (Adalet ve Kalkınma Partisi) and its leader Erdoğan would generate discomfort for an

audience who is supporter of the main opposition CHP (Republican People's Party). Festinger asserts that the easiest way to decrease dissonance is selective exposure, which means to seek out pro-attitudinal information and to avoid contradictory information and situations which have the potential to raise the level of dissonance.

Based on Festinger's cognitive dissonance theory, many scientists conducted studies to investigate people's information seeking behavior and to explain why people seek out political information that is consistent with their existing attitudes. In most of these studies, they examined the correlation between political leanings of people and the media sources (such as TV programs, newspaper articles, political brochures) which they selected in an experiment or survey (e.g., Lowin, 1967). While selective exposure is mostly explained as a means of reducing cognitive dissonance, some scholars argue that selective exposure might be exercised based on some other contexts. For example, as the availability of information sources increases, processing information in an effective way gets harder. Accordingly, selective exposure is regarded as a useful means to simplify this information process task (S. M. Smith, Fabrigar, & Norris, 2008). While seeking information, a *cognitive miser*, who wants to reach to a conclusion as fast as possible without exhausting too much cognitive resources, avoids counter-attitudinal information and exercise selective exposure to supportive information (Stroud, 2006). From this point of view, selective exposure is not motivated by attitudinal dissonance, but by the simplicity for processing supportive compared to non-supportive information.

On the other hand, given that some of the empirical research didn't find strong evidence in the past to associate psychological preferences with supportive information (e.g., Freedman, 1965), these mixed findings led a



new term to arise: *de facto selectivity*, meaning that instead of psychological and ideological motivations, it is some other factors such as the *availability of information*, which leads to selective exposure (Freedman, Jonathan L., 1966). For example, some people might read a particular newspaper just because that its magazine papers are highly attractive. But the political orientations with those people and with that of the newspaper might not match. Therefore, in this situation, engaging selective exposure to that newspaper doesn't stem from ideological or political alignment with it.

Although selective exposure thesis consists of both seeking out supporting ideas and avoiding challenging ones, some studies revealed that these two forms of selectivity are distinct. Different studies conducted in U.S. showed that people, who selectively expose themselves to attitude reinforcing political information are far away from avoiding themselves from attitude-challenging political opinions, which results in cross-cutting exposure (Garrett, 2009b; Garrett, Carnahan, & Lynch, 2011). While stronger partisanship is associated with greater selective exposure to opinion-reinforcing information, it doesn't associate with greater selective avoidance (Garrett, 2009b). Furthermore, the influence of reinforcing information is found to be more obvious on polarization than that of cross-cutting exposure (Taber & Lodge, 2006).

At first glance, these findings may seem to contradict with cognitive dissonance theory, which suggests that people try to filter out counter-attitudinal political information to reduce dissonance. But a revision of Festinger's cognitive dissonance theory explains this situation to a large extent. Frey (1986) suggests that counter-attitudinal information might be useful and desirable in various circumstances. For example, understanding the oppositional views in order to criticize and surpass it in a discussion

might be motivating for exposure to uncongenial information. Indeed, even if partisan selective exposure might not keep audiences from avoiding attitude-challenging information, past research shows that audience who have strong partisan attitudes hold their pre-existing predispositions even after exercising cross-cutting exposure to challenging information (Druckman & Bolsen, 2011).

Whether people are selectively exposed to cross-cutting or like-minded ideas and the extent of it is has great implications for political communication and democratic processes. To be able to evaluate both sides of a controversial issue, people should be exposed to cross-cutting views, which is also vital for encouraging political dialog and democratic citizenry (Habermas, 1989). Otherwise, exposing only to pro-attitudinal views would do no more than reinforcing pre-existing attitudes, and accordingly increasing polarization on a society. If not helps to change one's existing ideas, exposing to diverse opinions would at least give people opportunity to make empathy for contrasting ideas and to see their already-possessed position through the window of oppositional views (Mill, 1859). In a study, Mutz (2002) found that people who communicate with people from diverse political beliefs are better in understanding oppositional points of view. Furthermore, those people who are exposed to cross-cutting political ideas develop more political tolerance compared to people who live in politically homogeneous networks (Mutz, 2002). Thus, an influential way to decrease fragmentation in a society would be to promote social interaction and deliberation in both inter-personal and mass communication networks. In addition, reducing the level of selective exposure by exposure to cross-cutting ideas is also a good way to decrease fragmentation.

According to Mutz (2001), there are two contexts for being exposed to similar and dissimilar views. One is inter-personal communication, which is related to people's selectivity about having friends, and living in an environment with others who share the same predispositions with them. The studies show that people choose to live in environments that are consistent with their lifestyles, which is highly correlated with their political predispositions. Additionally, they prefer to discuss politics with people who share the same political affiliation with them (R. R. Huckfeldt & Sprague, 1995). These findings suggest a high level of selective exposure in terms of inter-personal communication habits in U.S..

The other context is mediated (mass) communication, which consists mainly of media sources to communicate with people or to get information. TV's, radio channels, newspapers, and internet are mass media sources that are available for everyone today. All these mediated environments offer people to get information about what is happening around. Furthermore, these environments offer people more ability, desire, and availability for selectively exposing themselves to any source.

While both provides opportunity for like-minded selective exposure, mediated exposure is regarded as more motive for cross-cutting exposure to counter-attitudinal information than inter-personal exposure. For example, many people might refrain from interpersonal political discussions on the grounds that they will encounter social pressure or disagreement. But, as containing no interpersonal discussion as well as ensuring anonymity, they might feel more comfortable for selectively expose themselves to dissimilar media sources (Diana C. Mutz & Martin, 2001).

There is a long-lasting debate on which context has more influence on political attitudes. While some scholars favor in one context, some others propose that these attitudes are the consequence of a dynamic process between political conversations and media consumption, which are complementary of each other (Yonghwan Kim, 2015). Although which context is more influential on attitudes is a significant issue, this thesis focuses on just one context, politically motivated selective exposure to media sources, which refers to the condition in which people tend to select information that reflect and support their political predispositions, and avoid politically-discrepant information as well (Garrett, 2009b). More specifically, this thesis aims to investigate to what extent Turkish people follow political news outlets and politicians that share the same political views with them on Twitter, and to what extent they “don’t follow” outlets and politicians that are clustered on the other side of the political spectrum.

### **2.1. Partisan Selective Exposure to Congenial Media Sources**

Selective exposure is a term aiming to theoretically explain why individuals make their media exposure decisions based on their attitudes and beliefs. Considering that people have many beliefs on many diverse issues, which belief is more motivating to decide on selective exposure is important. Studies show that political partisanship is a key cognitive construct which is chronically accessible when processing information (Green, Palmquist, & Schickler, 2004). Therefore, political partisanship is easily activated from memory and accompanies to selective exposure decisions.

As a transformation of selective exposure theory to political science, partisan selective exposure occurs when individuals choose to consume

political information which share their existing ideological and political views, and chose to avoid information that is regarded as politically attitude-challenging as well (Stroud, 2010). In line with these theoretical assumptions, previous studies on political communication has suggested that selective exposure to media sources is mostly motivated by political partisanship. Paul Lazarsfeld and his colleagues noted that:

Predispositions lead people to select communications which are congenial, which support their previous position. More Republicans than Democrats listened to Wilkie and more Democrats than Republicans listened to Roosevelt. The universe of campaign communications, - political speeches, newspaper stories, newscasts, editorials, columns, magazine articles, - was open to virtually everyone. But exposure was consistently partisan. The more strongly partisan the person, the more likely he is to insulate himself from contrary points of view (Lazarsfeld et al., 1944).

Bimber and Davis (2003) demonstrated that the voters are politically divided in terms of visiting presidential candidates' websites. As an indication of partisan selective exposure, Republicans were more likely to visit presidential campaign website which is supportive of George W. Bush, while Democrats tended to visit campaign website of the candidate Al Gore. Stroud (2010) showed that strong partisanship was the main reason behind the homogeneous media exposure. Based on the findings, she suggested that in addition to exposure to homogeneous social networks, exposure to homogeneous media sources would be a second indicator of political polarization. Similarly, Iyengar and Hahn (2009) documented that people exercise selective exposure to media sources which they perceive as sharing the same political affiliations with their ideological and partisan predispositions. More specifically, they found that democrats and liberals choose to read news report from CNN and NPR, which are regarded as left-leaning media sources, and they choose to avoid news reports from Fox

News, which is perceived as right-leaning. Moreover, the same partisan selective exposure behavior was also true for conservatives and Republicans, who read news only from Fox News and who avoid news from CNN and NPR as well. It might be argued that the degree of partisan selectivity might differ based on the issue (whether it is politically controversial or not). But the findings tell quite the opposite. Partisan selective exposure is still exercised even if the news coverage is not related to politics (Iyengar & Hahn, 2009). All these findings suggest that partisanship is a significant motivation in terms of partisan selective exposure to pro-attitudinal media sources.

On the other hand, there is a socially undesirable and negative perception about selective exposure to attitude-consonant information throughout the public. Studies show that people from both sides of the political spectrum, even who exercise partisan selective exposure to attitude-consonant information in their news diets reject their slanted exposure. While they identify their news diet as balanced and cross-cutting, they attribute partisan selective exposure behavior only to their political opponents. In line with the perceived selective exposure hypothesis, they assert that their political rivals mostly consume political news that are congenial for them (Perryman, 2017). A survey in Turkey also points to a high level of negative perception about selective exposure, with over three-quarter of all different party supporters (AKP, CHP, HDP, and MHP) claim they selectively expose themselves to news outlets that contradict their ideological view (Akyürek & Koydemir, 2014).

In an attempt to explain the underlying cognitive process behind selective exposure, Sunstein (2007) notes that there is a natural human tendency to consume news that are not attitude-challenging and that don't

disturb individual's political views. She gives an important example to this cognitive process. In her study, she found that people, when offered to choose among others, are three times more likely to choose an article which is labeled with an outlet that is congruent with their political view, even if the fictional content of that article supports just the opposite of that view (Sunstein, 2007).

Selective exposure thesis is revised based on some research findings. Studies conducted in U.S. argue that not all the mass public selectively exposes themselves to political difference. Instead, people who have stronger partisan feelings toward political parties and ideologies are more likely to consume consonant views and refrain from inconsonant views (Stroud, 2008). Similarly, Prior (2013) argues that selective exposure to like-minded news can be attributed to politically interested and active people, who consist of only a small but influential part of the whole population. He notes that political polarization is not a consequence for most of the audience, whose political attitudes are not affected by selective exposure and hence keep being moderate. In line with Prior, Mutz (2006) notes that moderate people are more inclined to expose themselves to diverse political views compared to partisan people. Therefore, empirical studies investigating the degree of selective exposure and its effect on political attitudes are pointing out to a significant variable; strength of partisanship, which is regarded to have a mediated role between selective exposure and political polarization (Stroud, 2010).

## **2.2. Partisan Selective Exposure to Online Media Sources**

Before the advent of internet and online media platforms, people used to be dependent on traditional and mostly mainstream media markets, which consisted mainly of TV channels and print newspapers with large circulation numbers. What's more, these outlets were appealing to the audiences that were from diverse sides of a political spectrum. Although involving cues about their political predisposition, the news content of these mainstream media sources was more balanced, less partisan, and included more contrasting point of views in their reports (Bennett & Iyengar, 2008). People who consumed these mainstream media sources were more or less able to read/watch different aspects of a political issue or a public debate.

With the transformation in online political information environment, various types of online news sources emerged. For example, web sites, political blogs, online discussion boards, news feeds, search engines, social media platforms such as Twitter and Facebook, and digital-only news outlets are all the consequence of this transformation in online communication sector. While providing great opportunity to choose among many, these new information environments also motivated people to engage in politics. For example, social media platforms such as Twitter and Facebook provide a great opportunity for this engagement. Each news outlet (either digital-born or print) has an account on these platforms. With no need to access its official website or to buy the print version, people who follow the accounts of any outlet in these platforms will be instantly informed about that outlet's news content. A recent survey conducted by



Reuters Agency in 2016 (Newman, Fletcher, Levy, & Nielsen, 2016) reveals that 73 percent of the Turkish respondents says they reach news via online social media platforms. This proportion is 54 percent for print newspapers, showing that Turkish audiences are turning to online media for news consumption. In line with it, the Reuters Digital News Report points out to the increase in digital-only news outlet consumption in Turkey, with 31% of respondents reading news from haberler.com, 22% from internethaber.com, 20% from ensonhaber.com, and 17% from haber7.com, all of which are born in digital media market and don't have a print version (Newman et al., 2016). Furthermore, that 64% and 30% of Turkish respondents say they share and discuss news via Facebook and Twitter respectively reveals the transformation and power of online news platforms among Turkish audiences. From this point of view, and in terms of selective exposure theory, this transformation means a lot for political scientists.

First, online media markets brought with them countless news outlets each of which offer diverse and even contrasting views. There are many *niche* digital-only outlets which represents only the views of a specific political party or ideology. Accordingly, when seeking out partisan content, people have less dependency on mainstream media which tends to be more balanced in their news reporting. They can choose to read any outlets which are similar with their political and ideological predispositions. They can also avoid outlets which reports attitude-discrepant information. Wider options in online media markets lead audience to choose the ones that are most suitable for them. This selection process promotes partisan selective exposure. On the other hand, being able to consume online information form wide range of political spectrum led audience perceive mainstream media as highly biased. As a result, they turned themselves into exploring

alternative and politically congenial information sources (Iyengar & Hahn, 2009).

Second, in this free information environment, many groups, even with extreme political ideas found the chance to make themselves and their ideologies heard, and they found supporters all around the world. This process motivated people who used to be politically dissimilar in their interpersonal networks, to gather around and talk with like-minded people in online echo chambers (Sunstein, 2007). Accordingly, this transformation, by exercising selective exposure to fragmented information environments, caused people who lived in heterogeneous communication networks to form online homogeneous networks.

On the other hand, with the change in online information technologies, the news reporting and consumption habits have also evolved. Balanced and diversified political opinions that were more or less observed in traditional media were under great risk with the online news outlets' enthusiasm to provide politically consonant news content to partisan audiences (Johnson, Bichard, & Zhang, 2009). In addition, during this process, online news markets have produced many large-and-small scale news outlets, which appeal not only to wide masses, but also to marginal and mostly partisan groups. As the online news outlets increased, so did the diverse political views that are represented by these mostly partisan "niche outlets". As Iyengar and Hahn (2009) notes, the dramatic increase in digital news outlets led to a more segregated information environment in which news outlets compete with each other to arouse the audiences' attention. Moreover, highly competitive media industry urges news outlets to appeal to the political dispositions of their audiences (Mullainathan & Shleifer, 2005). The outcome is the emergence of partisan

news outlets, which have less to do with journalistic norms such as objective and balanced reporting, and more to do with one-sided and slanted description of the facts (Levendusky, 2017). The availability of any online political information that are represented by those partisan outlets trigger people's selective exposure based on partisan orientations. Beside from selective exposure, less adherence to journalistic norms by those partisan news outlets allows party elites to disseminate their partisan messages (including reporting one-sided, hostile and uncivil arguments) throughout the media markets (Davis & Dunaway, 2016).

The technological developments in communication field also transformed the use of mobile phone as a mass communication tool. Especially, with the android-based applications of newspapers, people don't need to spare specific time for reading news from print-press newspapers or from their computers. A mobile phone with internet access makes it very easy to reach any news outlet at any time without paying any price. According to the Reuters Digital News Report (2016), among the Turkish respondents who use internet, 68 percent say they reach news via their smartphones, which increased by 11 percent compared to 2015. Thus, to appeal audience who reach news content via smart phone applications, even mainstream print newspapers are transforming themselves into online and digital enterprises.

Additionally, the ongoing increase in online media outlets' advertisement incomes (24.2% for Turkish online news outlets in 2016) and the ongoing decrease in print newspapers' advertisements incomes (14.8% for Turkish print newspapers in 2016) (Newman, Fletcher, Kalogeropoulos, Levy, & Nielsen, 2017) also motivated small-scale entrepreneurs to publish digital-only news outlets. Accordingly, in Turkey, there are many digital-

only outlets that don't have a print version. To mention but a few, t24 (a total of 969.000 followers on twitter), odatv (893.000), haber7 (878.000), and diken (696.000), are reporting news national wide and have much more followers from most of the legacy newspapers (e.g., *Aydınlık*:300.000, *Diriliş Postası*:57.000, *Güneş*:349.000, *Milat*:90.000, *Yeniakit*:145.000, *Yurt*:192.000) that have a print version. The perception of mainstream media as controlled and pressured by the government in Turkey appeal audiences to turn toward these online news portals, which are regarded as having less pressure and more free journalism practices (Newman et al., 2017). From this point of view, this thesis also aims to investigate whether Twitter accounts of Turkish print newspapers differ than that of the Turkish digital-only news outlets in terms of attracting partisan selective news exposure.

On the other hand, online media platforms enabled the audiences - who used to be passive in consuming traditional news - to actively engage in politics by both consuming news from diverse perspectives, and by involving in online political discussions. Indeed, as people gather more information about a political issue from news outlets, they talk and discuss much more about it (Brundidge, 2010). All the online news outlets, and social media platforms such as Facebook, Twitter and *eskisozluk.com*, enable their audiences to engage in political discussions by creating them a comment space under each news/topic for writing their opinions about it. Moreover, people can engage in a political debate with anonymous users via this comments that is adjacent to any political news content. Thus, political engagement on online platforms has the potential to motivate people further to discuss and express their political views, which is thought to increase level of partisan selective exposure and polarization.

### **2.2.1. Twitter as a Medium for Attracting Partisan Selective Exposure**

Twitter is a popular online news and social networking service in which its users can send and receive text-based posts (tweets) that are less than 280 characters. As Twitter is a public micro-blogging site, joining into it simply requires signing up with an e-mail, choosing a user name to use and designing the Twitter home page such as uploading a profile photo and adding a short biographical information.

The act of tweeting simply means sending a short message to anyone who follows you on Twitter. Tweets are used for many reasons, which include professional and amateur news reporting, opinion sharing, marketing and advertising, social messaging, status-updating, posting interesting ideas and links, discussing and even making political propaganda. Hyperlinks, mentions and hashtags can be added into these tweets. A hyperlink, - *which is activated by clicking on the highlighted url within the tweet*, directs the Twitter users to another location. It is mostly used by the news outlets to direct the reader to the original news where the full content is published. Indeed, on Twitter, almost all news outlets send in their tweets a short title/brief explanation of the news item and give a link to the original news in their web-site. Mention is a tweet containing another account's Twitter username, preceded by the "@" symbol. It is used to draw the attention of another Twitter account. A Hashtag is a keyword or a phrase used to describe a topic or a theme. For example, "#weloveerdogan" is a hashtag, which is used to express support for the president Erdoğan. To create a hashtag the pound sign (#) must be put before the word or phrase. A hashtag automatically becomes a clickable link when it is

tweeted. Anyone who sees the hashtag can click on it and be brought to a page featuring the feed of all the most recent tweets that contain that particular hashtag. Twitter users put hashtags in their tweets to categorize them in a way that makes it easy for other users to find and follow tweets about a specific topic or theme.

Following someone on Twitter means to get their latest tweets in your Twitter feed. Similarly, being followed by someone enables them to get your tweets in their feeds. As Twitter is an instant messaging application which can be constantly updated, this feature makes it a very powerful journalistic tool. Following favourite news outlets and their reporters/journalists on Twitter makes their most recent news items, columns and comments available to their followers. This motivates the Twitter users to follow like-minded news outlets and journalists on Twitter which share the same political views with them. At the same time, these users can easily avoid any challenging information by simply not following outlets that are politically counter-attitudinal. As Himelboim et al. (2013) notes, Twitter users practice a large amount of partisan selective exposure by following like-minded Twitter accounts. Moreover, they are unlikely to be exposed to cross-cutting political information as their follower and followee networks are politically homogeneous. Likewise, Halberstam and Knight (2016) note that Twitter users are disproportionately exposed to attitude-consistent political information on Twitter, which implies partisan news selectivity on Twitter.

In sum, as an online communication and news reporting platform, Twitter enables politically more fragmented media environment, which motivates its audiences to seek out like-minded news and to avoid challenging content. Therefore, this study investigates whether and to what

extent Twitter is an appropriate medium to attract partisans and to motivate them for selective news exposure in Turkey.

### **2.3. Predictors of Partisan Selective Exposure**

What drives people to consume only like-minded news outlets and wall themselves off from attitude-discrepant outlets? Studies demonstrate that there are some factors that predict and have an impact on selective exposure. As a main predictor, the strength of attitude is strongly correlated with the process of selective exposure to attitude-consistent information (Petty & Krosnick, 2014). For example, when confronted with an attitude-discrepant information, a more extreme attitude would produce higher levels of cognitive dissonance and accordingly higher levels of selective avoidance (Knobloch-Westerwick & Jingbo Meng, 2009). Likewise, an issue which is regarded as highly important is more likely to be selectively exposed. Thus, factors such as partisanship, political knowledge, interest, engagement and participation, media fragmentation, and news use frequency which are closely related to attitude-strength would be significant predictors in terms of selective exposure to politically like-minded news outlets.

#### **2.3.1. Political Interest**

Interest in politics is strongly related with partisan selective exposure. People who are interested in politics tend to get much more information which reflect their political predispositions compared to the less-interested ones (Stroud, 2006). As people get more interested in politics, they seek out more information to reinforce their political attitudes. Lazarsfeld and his colleagues revealed that greater interest in politics

increased the likelihood of partisan selective exposure compared to the less political interest (Lazarsfeld et al., 1944).

### **2.3.2. News use frequency**

The frequency of news use is also an indicator for partisan selective exposure. In an experimental study, participants who consumed more news in general, selected attitude-consistent political news content more strongly compared to participants with low news-consumption frequency (Knobloch-Westerwick & Jingbo Meng, 2009).

### **2.3.3. Political engagement and participation**

It can be said that, searching political information, participation to online political communities and discussion groups, sending messages to other audiences, writing comments about news content on social media platforms, following political news outlet accounts, retweeting their messages, liking and disliking a content about a political issue, mentioning someone in a Facebook or Tweeter post are all linked with political engagement. This part of the population is the most likely to cast vote in elections, to contact with politicians, to discuss political issues with others and to participate into political activities such as party meetings, conferences, campaigns, and donations (Thornal, 2015). Wojcieszak (2009) found that higher levels of participation in ideologically homogeneous discussion groups on Internet predicted higher levels of political engagement. He also argued that selective exposure to politically heterogeneous interpersonal networks (family and friends) decrease the level of political engagement among online homogeneous discussion groups (Wojcieszak, 2009). Likewise, political participation in offline communities is found to influence selective exposure to congenial information in online communities (Dutta-



Bergman, 2006). Prior's (2007) findings also highlight the importance of political engagement in partisan selective exposure processes. He notes that the dramatic increase and fragmentation in political news outlets led politically engaged partisans to form echo chambers in their news consumption habits. These findings confirm the suggestion of Iyengar (2009), who notes that political engagement is a significant predictor of selective exposure to congenial news outlets. This prediction might be both in deliberative and nondeliberative communication contexts. Someone who is interested and informed in politics, who participate in political communities and who engage in political activities tend to exercise greater partisan selective exposure when consuming political news and when engaging in online political discussions (R. Huckfeldt, Mendez, & Osborn, 2004).

#### **2.3.4. Political Knowledge**

Past studies reveal that political knowledge also predicts partisan selective exposure (Chaffee, Saphir, Grap, Sandvig, & Hahn, 2001). One explanation of this relationship is that politically knowledgeable people are more consistent with their pre-existing attitudes and beliefs. The more being knowledgeable about a political issue, the less need to search for contrasting views about it. Therefore, people with higher knowledge about politics tend to exercise more selective exposure to news outlets that are congenial with their existing political predispositions (Stroud, 2006)

Moreover, exercising selective exposure based on preliminary political dispositions requires political knowledge enough to recognize political cues. Being aware of which media outlet serves to which political

ideology is one of the basic prerequisites to engage in partisan selective exposure.

### **2.3.5. Strength of Partisanship / Ideology**

Partisanship and ideology are also important driving forces behind partisan selective exposure process (see e.g., Green, Palmquist, & Schickler, 2004; Meffert, Chung, Joiner, Waks, & Garst, 2006). Past research has revealed that partisan selective exposure increases polarization especially among the people that have higher levels of political partisanship (e.g., Stroud, 2010). The main reason that the strength of partisanship influences partisan selective exposure is the fact that people with a strong political affiliation tend to seek out supportive information about their political candidate or political issue (Johnson et al., 2009). Furthermore, greater consumption of politically consistent online news among strongly partisan audience promote less exposure to online news that are slanted away from their political views (Garrett et al., 2011). The close relationship between partisanship and selective exposure refers to a mutuality between two of them. People who have strong partisan feelings toward a party or ideology might be motivated to exercise higher levels of selective exposure to media sources with which they share the same political views. Alternatively, engaging in selective exposure to like-minded media sources might make people more partisan and polarized.

Slater (2007) explains this mutual relationship between media selectivity and its effect on partisanship as “reinforcing spirals”. According to this framework, there is a reciprocal relationship between partisanship and media selectivity. On one hand, partisanship and strength of ideology effects the degree of media selectivity; the more partisan an audience,

greater the degree of partisan selective exposure. On the other hand, greater selective exposure to congenial media because of preliminary partisan leanings increases the level of partisanship and ideology, which in turn leads to more selective exposure to politically consonant media news. This reinforcing spiral process leads to a spiral of continuous and complementary influence among media selectivity and political attitudes (Slater, 2007). From this point of view, both these variables (selective exposure and partisanship) mutually reinforce each other. They can be antecedent/consequence of each other, and can be regarded as a predictor and an outcome at the same time.

As seen, the direction of the causal relationship between selective exposure and partisanship is not clear. But some studies revealed that selective exposure combined with partisanship evidently leads to political polarization (Stroud, 2010). The logic behind this assumption is that when selective exposure on the basis of partisanship occurs, each exposure to like-minded information make the existing political attitudes more extreme and solid. Therefore, partisan selective exposure leads to greater polarization in the audiences.

### **2.3.6. Media Fragmentation**

The level of partisan selective exposure differs for each country based on its society's media environment and the level of media fragmentation. In countries with a high level of press-party parallelism, there exists many newspapers that are representative of each party and ideology. Therefore, media slant becomes evident for most of the audiences, which makes them easier to select an outlet which is consistent with their political and ideological predispositions. On the other hand, in countries

where media is tended to be more mainstream and to present different sides of the controversial political issues with a balanced content, people have difficulty in perceiving the political leaning of a newspaper, and accordingly might not decide upon which outlet to read for reinforcing their predispositions.

A comparative study showed that compared to U.S., where newspapers are regarded as reporting political news with a more balanced and objective content, Britain newspapers have a higher level of slant toward political parties. Accordingly, people have a higher level of partisan selective exposure by being less exposed to challenging political views in UK (Diana C. Mutz & Martin, 2001).

Scholars emphasize that selective exposure and its effects on polarization are strongly related to the media system in a country. Different media landscapes and political contexts may produce different journalistic norms and reporting standards in different countries (Yang et al., 2016), which affect the level of political parallelism and hence partisan selective exposure in a media environment. For example, consuming partisan news is strongly related to oppositional media hostility, which refers to a condition where people consuming like-minded media define counter-attitudinal media sources as unreliable, hostile, quarrelsome and unfair (Arceneaux, Johnson, & Murphy, 2012). Therefore, in countries where media markets have higher levels of political affiliation and partisanship, as well as less civility norms and objective reporting standards, greater partisan selective exposure would be expected in the audience.

In his comparative media system research, Hallin (2004) argues that countries that fit into the Polarized Pluralist model such as Greece, Italy and

Spain have a media environment that have high levels of political parallelism, which is defined as the strong alignment of news sources with political parties. He suggests that in Polarized Pluralist media systems, media environment becomes highly polarized, which is a strong reflection of wide political spectrum of that country. In line with Hallin, Horwitz and Nir (2015) argue that as the political parallelism increases in a media system, the relationship between selective exposure and partisanship gets stronger. More clearly, because the chances that an audience can come across to a partisan message on media would increase, more political parallelism in a media landscape leads to more *de facto* selectivity, whereas less political parallelism leads to more cross-cutting news exposure, even unintentionally (Horwitz & Nir, 2015).

Indeed, a survey conducted in Netherlands, whose media system is categorized as Democratic Corporatist Model by Hallin (2004) (*this media system involves no political parallelism, high external pluralism and neutral journalism*), found no relationship between selective exposure and polarization in Dutch respondents (Trilling, van Klingeren, & Tsfati, 2017). The absence of this relationship is mostly because Netherland's media system doesn't harbor a political parallelism, nor its mostly moderate audience take news content that is extremely partisan slant too seriously.

On the other hand, Turkish media system is regarded as involving high political parallelism with a politically polarized media, where conservative newspapers such as Sabah and Star have considerably positive slant towards the ruling AKP and negative slant towards the main oppositional CHP; and whereas opposition newspapers such as Cumhuriyet and Sözcü have considerably positive slant towards CHP and negative slant towards AKP (Çarkoglu, Baruh, & Yıldırım, 2014). Sayarı

(2007) associates this polarization in media with Turkey's distinctive party system, in which parties have strong influence and institutional ties over media sector. Therefore, considering Turkey's highly fragmented, party-associated and politically polarized media system, this thesis expects that Turkish Twitter audience practice high levels of selective exposure to likeminded outlets and selective avoidance to politically discrepant outlets. On the contrary, it expects that users identified with a political party practices low levels of cross-cutting news exposure on Twitter. In accordance with the literature, this thesis also hypothesizes that, irrespective of the favored party, there is a positive association between strength of identification and like-minded news exposure, and a negative association between partisanship strength and cross-cutting news exposure.

#### **2.4. Potential Effects of Selective Exposure for Democracy and Politics**

Online media's potential to increase selective exposure lead to great deal of interest and concern about its evolutionary effects on political attitudes. Basically, these concerns focus around Internet's potential to draw away from deliberative democratic concepts such as diversity and plurality (see e.g., Sunstein, 2011).

At first glance, the internet, -especially online information and discussion platforms-, is regarded as a positive development for democratic and public deliberation. The more people discuss on political issues, the more the opposite sides gain the ability to empathize with counter perspectives and hence come to a better and joint conclusion. Indeed, some scholars optimistically argue that Internet and online communication

platforms lead to cross-ideological exposure, which in turn contributes to political heterogeneity, decrease polarization, and have a significant impact on people's vote choices and political orientations. Thus, for these scholars, internet is regarded as an opportunity for plural democracy, political participation, opinion diversity, political tolerance, empathy for competing ideas, consideration of alternative viewpoints, and political consensus (see e.g., Brundidge, 2010; Dahlgren, 2005; Dilliplane, 2014; McKenna & Bargh, 2000; Diana C. Mutz, 2002; Papacharissi, 2002). Furthermore, there are some limited evidence suggesting that the Internet and online communication platforms don't induce selective exposure and selective avoidance. A survey conducted by Pew Research Center in U.S. revealed that even in a campaign season when polarization is expected to be in its highest level, Internet users did not isolate themselves to communicational echo chambers, and they were more selectively exposed to uncongenial information than non-users (John Horrigan, Kelly Garrett, & Paul Resnick, 2004). According to that survey, 18 % of American audiences preferred media sources that challenge their political views. Similarly, some studies found that people don't tend to isolate themselves from incongruent views on online communication platforms. Instead, they chose to consume news and discuss politics with people from dissimilar political views (see, e.g., Brundidge, 2010; Hargittai, Eszter., Gallo, Jason, & Zehnder, Sean, 2005). Moreover, the diversity of views and audiences encountered online is enjoyed and much appreciated by many people who uses Internet (Stromer-Galley, 2003).

While noting these positive sides of online media use, most of the current research results warn about increasing online media use in terms of its negative consequences to democratic processes. While regarded as a

technological breakthrough in mass communication field, these online platforms and the radical change in news consumption habits raises concerns about social fragmentation and political polarization (see e.g., Sunstein, 2002). In a society, where exposure to only attitude-consistent information and avoidance of counter-attitudinal information dominates political communication, attitude changes based on consuming media hardly occurs, and the society becomes more likely to be fragmented into mutually hostile political camps. In such a fragmented network, where cognitive dissonance prevails public deliberation, that kind of a partisan selective exposure behavior endangers democratic systems by making audiences more persistent in sticking to the preexisting ideological or political attitude, no matter it is rational or not (Mutz & Martin, 2001)

Accordingly, Prior (2007) warns that online media markets encourage audiences who are already interested in politics to sort themselves into fragmented media echo chambers, which in turn increase their level of political polarization. As a result of this fragmentation, people tend to selectively expose themselves to like-minded news, and discuss politics with people who share the same political predispositions with themselves. Similarly, they avoid being exposed to contradictory views and politically dissimilar people. For example, a study revealed that more than 50% of online blog users exercised selective exposure to politically consonant blogs, while this rate was only 22% for blogs with an uncongenial slant (Johnson et al., 2009). Some might argue that selective exposure might be exercised not on the basis of outlet-level, but on the basis of story or article level instead. But the results of a study suggest just the opposite. Gentzkow and Shapiro (2011) conclude that there is not a statistically



significant difference between ideological selective exposure to news outlets and to the stories that these outlets report.

These findings project light to a dangerous fragmentation in both social and media consumption contexts. Sunstein (2007) points to a media fragmentation which is generated by selective exposure to ideologically consistent media. She suggests that fragmentation on society based on diverse communication and media consumption habits have a strong potential to breed attitude extremism, polarization, and even violence and hatred. She also suggests that selective exposure to like-minded news and selective avoidance of contradictory views on Internet lead audience, who are not originally fixed in their political opinions, and not so fragmented, to move toward extremely separate positions, just because of what they consume in their news diets (Sunstein, 2007).

Similarly, Bimber and Davis (2003) warns about the possible consequences of partisan media exposure. They argue that selectivity toward attitude-consistent political messages on Internet reinforce partisan messages, mobilize politically active audience and strengthen partisan's political views. They also note that this partisan media exposure encourages people to sort into socially fragmented clusters in which people have communication only within their own clusters (Bimber & Davis, 2003).

As Internet and online media markets provide more news options for audience to choose and to avoid, the potential of online news to breed political polarization would be greater than offline and traditional media sources. As an example, new communication platforms offer people news feeds that are only congenial with their political dispositions. Pariser (2011) illustrated that partisan selective exposure in online platforms is becoming

much more an indispensability than an individual selection. Some social media platforms such as Facebook, Yahoo News and Google use some algorithms to produce personalized search results and news feeds. These algorithms guess the political predisposition of each user. Accordingly, they offer political information, social networks and news content that are only congenial to their users. Moreover, these prediction engines automatically filter out challenging and contrasting information from the audience's screens, which is defined as the filter bubble (Pariser, 2011). As was argued by Sunstein (2007) years before Pariser, the danger of emerging IT technologies is to motivate audiences to restrict themselves to echo chambers and to isolate themselves from contrary views, which undermines mutually understanding the views of other-side and solving social problems.

Online media platforms are not the only media sources that promote polarization. Selective exposure to other pro-attitudinal media sources such as cable news promotes ideological polarization as well (Lin, 2009). But by offering many options to choose, internet goes far beyond in terms of triggering selectivity and partisanship. As Baum and Groeling (2008) and Gentzkow and Shapiro (2011) note, political and ideological fragmentation in online media platforms such as blogs and news websites are higher compared to traditional news sources such as print newspapers. In line with these scholars, traditional sources of media such as TV news and print newspapers are found to create greater exposure to cross-cutting information than online media sources (Diana C. Mutz & Martin, 2001). As offering great amount of diverse political information, and as enabling their audiences to select whatever news outlet or content to read or avoid, online

social media environments such as Facebook and Twitter might breed greater partisan selective exposure.

Although empirical findings in U.S. are mixed about to what extent this threat is real (Markus Prior, 2013), this thesis aims to find an answer to this question in Turkish Twitter users' context. To what extent like-minded/partisan news consumption and political polarization phenomena is real in Turkish Twitter medium? Those who practice selective news exposure and who are politically polarized are only a small fraction of the Twitter population, or these practices pertain to a large Twitter audience from all sides of the political spectrum? Does supporting a specific political party affect these practices, or do they pertain to audiences from all four political parties? What is the digital and print media's position in terms of attracting audience that exercise like-minded and cross-cutting news exposure. And most importantly, is there a relationship between consuming like-minded news outlets and having politically polarized attitudes? Likewise, is there a relationship between consuming cross-cutting news outlets and having moderate attitudes?

To answer those research questions, this thesis focuses on Turkish Twitter users' selection and avoidance preferences of political news outlets, both digital and print, which is assumed to reflect their level of partisan selective exposure. By following a news outlet that have an account on Twitter, a Twitter user selectively exposes herself to the content of that outlet, which is expected to be consistent with her own political views. On the other hand, by not following a news outlet on Twitter, the same user selectively avoids the content of that outlet, which is expected to be slanted away from her political views. Thus, in a highly fragmented media environment, Twitter users' selectivity toward some specific outlets imply

not only their degree of selective exposure, but also their degree of selective avoidance. This selectivity toward party-associated and neutral/mixed news outlets also imply the partisan effect on this selectivity. Moreover, this thesis also aims to investigate the relationship between partisan selective exposure and its one of the most feared outcome, political polarization.

## CHAPTER 3

### POLITICAL POLARIZATION

Political polarization means reinforcement of an individual's positive attitude toward supported political view, and reinforcement of negative attitude toward the oppositional view as well. In other words, partisans who have most positive attitudes toward their own party and who have most negative attitudes toward the oppositional parties would have most polarized attitudes (Tsfati & Chotiner, 2016).

In line with the Festinger's (1954) social comparison theory, people adjust their opinions according to the dominant in-group opinion by making a comparison. As group disagreement decreases self-confidence whereas group agreement increases it, most people, who seek affirmation from the in-group which they belong to, tend to change their opinion that seems discrepant among the group members (Leon Festinger, 1954). Accordingly, changing an opinion which is regarded as discrepant for the majority of the in-group leads to polarization among diverse groups.

A politically polarized individual is maximally favorable toward a preferred political party/leader and maximally unfavorable toward a disliked alternative (Stroud, 2010). Therefore, political polarization is measured by considering the degree of favorability toward both supported and oppositional political parties. The highest degree of polarization means highest favorability toward pro-attitudinal party and no favorability toward counter-attitudinal party or parties.

### **3.1. Dimensions of Political Polarization**

There are two different dimensions of political polarization (Fiorina & Abrams, 2008). The first dimension, which is elite polarization, refers to the strength of political attitudes among political party elites. These elites include political party leaders, deputies, high-rank politicians, bureaucrats, influential political opinion leaders and powerful lobbyists as well. These elites dominate decision making processes in a political system. Elite polarization refers to a situation where elites of opponent political parties go extremes on political activities, such as incivil political speeches and absence of political tolerance against the opposition. Much of the studies in the literature found that the level of elite polarization is significantly increasing (e.g., Jacobson, 2003; McCarty, Poole, & Rosenthal, 2016).

The second dimension, which is mass-level polarization, refers to the polarized partisan attitudes that is visible throughout the public (Lelkes, 2016). Mass-level polarization involves not only favorability toward supported party, but also unfavourability toward the oppositional party. Some of the past studies show that just like the elite polarization, mass polarization is also on the rise (e.g., Jacobson, 2003). Abramowitz and Saunders (2008) conclude that elite polarization based on ideological lines in U.S. reflects mass polarization among the public. They find evidence that polarization is not confined to a small group of political activists, but to a larger part of the mass population (Abramowitz & Saunders, 2008). This relationship between elite and mass polarization is explained by the argument that greater ideological polarization in Congress-Parliament and among party elites clarifies the ideologies and positions of political parties

in the mass public's perception, which simplifies for the ordinary electorate to follow political and ideological cues, and which in turn creates a more partisan voter (Hetherington, 2001). A recent survey conducted by Reuters Agency in 2017 points to a high level of polarization among Turkish people based on ideological lines. Reuters Digital News Report (2017) notes that Turkish people are politically polarized between adherents of Islamism and supporters of Kemalism.

Bishop (2009) illustrates that the increase in political polarization caused even wider social division among American citizens, with people creating politically homogeneous relations and sorting their living places, clubs, civic organizations and even churches according to their political predispositions. Considering that the ruling party AKP and the main opposition party CHP get strongly dominant votes from diverse geographical regions throughout Turkey, it can be assumed that political polarization based on geographical segregation is also true for Turkey.

However, some other studies contest this view by citing that elites are not successful in convincing their party supporters to have more extreme political attitudes and positions like them against the opposition (Levendusky, 2009). They argue that in general, citizens hold centrist positions in most of the controversial political issues (Fiorina & Abrams, 2009). Those who are politically polarized are limited to political activists, who have high level of political interest and engagement (Fiorina, Abrams, & Pope, 2005; Markus Prior, 2013). While acknowledging partisan selective exposure phenomenon, these scholars argue that due to the increased media choice, when given the option, most non-partisan moderate people either turns out partisan media sources or exercise cross-cutting exposure to counter-attitudinal news sources, which minimizes the effects of partisan

media and hence polarization (Thornal, 2015). As seen, there is an academic debate whether and to which extent there is a mass level political polarization in societies. Thus, the mixed findings about the extent of mass polarization also raise the questions about the measurement of polarization in academic studies.

When it comes to Turkey, polarization becomes a key variable that explains Turkish political system. As Kiriş (2010) notes, high level of elite polarization among rival political parties increasingly consolidates the electorate in Turkey and forces them to disassociate from the opposition and become a more loyal voter to their own parties. That kind of a polarization finds its expression in president Erdoğan's famous remarks in 2010; "Those who don't become a party become eliminated" (taraf olmayan bertaraf olur). Just as Erdoğan implies, the moderates in a politically polarized society increasingly feel the pressure from both sides of the rival political camps, and face the risk of elimination from public and political life (Kiriş, 2010).

While all political systems harbor political polarization at least to some extent, polarization in Turkey embrace quite different implications. Bilgiç et al. (2014) argue that polarization in Turkey carries the potential to threaten social peace, inter-group justice and public security. He also warns about the possible relationship between polarization and inter-group injustice, discrimination, identity and ethnic-based conflicts in Turkey (Bilgiç et al., 2014).

### **3.2. Indicators of Political Polarization**

Mass level political polarization can be measured in several ways. Most of the studies use certain indicators for measuring political



polarization such as partisan polarization, ideological polarization, issue-based polarization and affective polarization.

### **3.2.1. Partisan Polarization**

Partisan polarization is one of the most commonly used indicator to measure political polarization. As citizens' strength of party identification toward political parties increases, so does the political polarization (Gentzkow, Matthew, 2016). In her distinguished study, Stroud (2010) uses partisan polarization to measure polarization among audiences. More specifically, she asks respondents to give a score to rival presidential candidates, Bush and Kerry, ranging from 0 (very unfavorable) to 10 (very favorable). She operationalizes polarization as the absolute value of difference between scores of two rival party candidates. For example, while an electorate who gives a 10 score to Bush and 0 score to Kerry is maximally polarized for Republican Party, another electorate who gives 5 to both candidates is regarded as moderate.

Considering that U.S. has a two-party system in which two rival parties, Democrats and Republicans compete for elections, it is possible to measure partisan polarization by capturing bipolar attitudes about two competing political sides. However, Turkey has a multi-party system, with tens of political parties competing on elections, and with four major parties (AKP, CHP, HDP and MHP) having a seat on parliamentary. Therefore, although the most accurate, it would be much more challenging to capture each partisan's favorability score toward to each political party, and followingly measure partisan polarization. As an alternative, partisan polarization in Turkey might be measured based on being either pro-government or oppositional, which compares the feeling thermometers

toward the ruling AKP on one-side and toward the oppositional parties (CHP, HDP and partly MHP) on the other side. Indeed, in a country where polarization is peaked on the basis of supporting or opposing government (Dr. Salih Akyürek & Fatma Serap Koydemir, 2014) people's strength of political stance for or against the government might significantly point to political polarization.

The surveys on partisan polarization reveal a high level of polarization in both U.S. and Turkey. For example, in U.S., a survey showed that while the difference between favorability scores toward own party and opposition party was nearly 30 for both Democrats and Republicans on a 0-100 scale, this difference has recently increased above 85, implying a clear political polarization based on partisan identification (Pew Research Center, 2014). On the other hand, a recent survey shows that favorability toward pro-party leaders are also quite high in Turkey. Favorability toward AKP leader Erdogan, CHP leader Kilicdaroglu, HDP leader Demirtas and MHP leader Bahceli are 85 percent, 50 percent, 82 percent and 45 percent respectively. (Institutional Social Responsibility Organisation, 2016). Moreover, on average, each four party supporters have less than 5 percent favorability toward other party leaders, projecting to a higher level of partisan polarization among Turkish partisans compared to U.S.

### **3.2.2. Ideological Polarization**

Besides from partisanship, ideological segregation is also a significant predictor for political polarization. Considering that ideological predispositions are one of the significant factors contributing to the party identification, some studies regard ideology strength as having a better

effect in measuring attitude extremity and political polarization (Garrett et al., 2011).

Abramowitz and Saunders (1998) find a strong political polarization based on ideological divisions. In U.S., there are two competing political parties, the Democratic Party and the Republican Party, which are closely aligned with two competing ideologies, liberalism and conservatism respectively. Their study demonstrates that, as suggested in ideological realignment theory, people in U.S. increasingly identify themselves with a political party based on their ideological predispositions, suggesting that ideological preferences have become strong motivations for political participation and polarization (Abramowitz & Saunders, 1998).

While many political systems (such as in U.S.) are divided based on left – right ideologies which refers to liberalism and conservatism, there are more ideological lines in Turkish political spectrum that exists in left-right wings. As such, each wing harbors diverse ideological contexts within itself. Consequently, four major parties differ in representing distinct specific ideologies that operate within left and right ideologies. Moreover, in Turkey, the meanings attributed to these left (liberal) and right (conservative) wings are a bit different. For example, the ruling AKP represents Political Islamism and conservatism, which is associated with right-wing ideology. The main oppositional party CHP represents secularism, social democracy and Kemalism; and another oppositional party HDP represents socialism and ethnic Kurdish ideology, both of which can be associated with left-wing ideology. However, the third oppositional party that have a seat in Turkish parliament, MHP, represents nationalist ideology, which is completely against the left-wing ideology, and which can be associated with right-wing ideology.

Considering MHP party executives' recent and increasing convergence with the ruling AKP in many political issues including much-debated presidential system and Afrin military operation, and CHP and HDP's long-standing alignment in many issues as well as their joint and strong opposition to the ruling AKP, it would make sense to measure "elite polarization" in Turkey on the basis of right-left ideological segregation, where the former represents conservatism, Islamism and nationalism; and the latter represents secularism, Kemalism, socialism, and socio-ethnic community values such as Kurdism, Alevism, atheism and LGBT. However, the recent separation of a fraction within MHP who constituted İyi Parti and considering the indecive position of MHP grassroots in terms of supporting the ruling party casts doubts on the position of MHP voters in measuring mass level left-right ideological polarization.

A survey documents that 53 percent of pro-AKP respondents and 51 percent of pro-MHP respondents identify themselves as right-wing, which is 6 percent and 4 percent for respondents who supports CHP and HDP respectively. Similarly, 26 percent of CHP and 42% of HDP supporters self-identify as leftist, which is only 2 percent and 5 percent for MHP supporters respectively (Akyürek & Koydemir, 2014). Taken together, these findings suggest that, the supporters of parties stick to the ideologies which are represented by their parties. However, sharing same ideologies (i.e. left and right) in a range of political spectrum might not necessarily mean sharing same positive feelings toward out-parties that represent these ideologies, which is especially in question regarding right-wing ideology.

### **3.2.3. Issue-Based Polarization**

A third indicator of political polarization is the division of mass public based on controversial political issues. In societies with less political polarization, issue positions might be a better way to capture political attitudes. Strong support or opposition to some controversial political issues hint for the strength of attitudes. For example, in U.S., political issues such as abortion, health care, tax policy, homosexuality, military policy, gun ownership and global warming are used to measure the degree of extremity in taking positions on these controversial issues. The studies reveal that there is an increasing polarization in American public based on issue-positions, meaning that Democrats and Conservatives hold extremely different positions about controversial political issues (Pew Research Center, 2014).

It is a public perception to think that issue-based division is even deeper in Turkey, with supporters of ruling and the opposition parties hold extremely polarized positions on some controversial political issues such as presidential system, State of Emergency Decrees, military activities about Syria, education policies, corruption, homosexuality, gender and ethnic discrimination. For example, a survey carried out by Gezici research company in Turkey revealed that, 48 percent of the people are against the presidential system and 51 percent are supporting it, which nearly corresponds to the amount of voters who are opposing and supporting the ruling party respectively (Gezici Research Company, 2017). Interestingly, the survey revealed that 80 percent of the electorate have no idea about the content of the constitutional change for presidential system that will be

voted in referendum, nor they wonder about it, meaning that positions taken on hot-debate issues are excessively determined by their parties' positions on those issues. On the other hand, that over three quarters of the people who define themselves as right-wing (83 percent) and conservative (77 percent) say they will vote for the presidential system, and that over three quarters of the people who define themselves as social democrat (78 percent) and leftist (89 percent) say they will vote against it, demonstrates that political polarization is very strong in ideological lines in Turkey. Furthermore, only 5 percent of the AKP supporters say they will vote against; and 4 percent of the CHP supporters and one percent of the HDP supporters say they will vote for the presidential system referendum in 16.04.2017 reveals that political partisanship is strongly associated with issue-based polarization in Turkey.

As Gentzkow (2016) notes, which political party we support and which ideology we are aligned with predicts our position about a political issue. Indeed, Dimensions of Political Polarization in Turkey (2016) survey results show that on many political issues ranging from Gezi Protests in 2013 to presidential elections in 2016, opponent party electorates get extreme and polarized positions. For instance, while 73 percent of CHP supporters define Gezi Protests as a peaceful reaction against government policies, 83 percent of AKP supporters define it as a conspiracy of external powers to overthrow the government. The survey also reveals that even positions toward non-political issues are identified in line with partisanship. For example, while 73 percent of the ruling party AKP's supporters believe that economic condition in Turkey is in progress for the last five years, only 7 percent of CHP supporters believe so.

### **3.2.4. Affective Polarization**

Another indicator of mass partisan polarization is the division of mass public based on their affections toward own parties and towards the opposition parties. Affective polarization is based on emotional reactions to party identifications. It has at least two dimensions: favorability ratings of “in-party” and “out-party” leaders/ supporters and social distance from the opposed party.

The first dimension of affective polarization is measured by taking the absolute difference of the values of positive feelings toward the supported party leaders/supporters, and negative feelings toward the disliked and oppositional party leaders/supporters. To measure these feelings, some emotional identifications such as patriotic, intelligent, honest, open-minded, generous, close-minded, hypocritical, selfish, and mean are used. How people identify their own party leaders/supporters, as well as opposition party leaders/supporters show the level of affective polarization. For example, in U.S., people who believed that their in-party members were intelligent increased from 30 percent in 1960 to 60 percent in 2008. This proportion decreased from 25 percent to 10 percent for out-party members. Furthermore, people who believed that out-party members were selfish increased from 20 percent in 1960 to 45 percent in 2008 (Gentzkow, Matthew, 2016). Another study also showed that as of 2014, 27 percent of the Democrats believe that Republicans are “a threat to the Nation’s Well-Being”, while this proportion is 36 percent for Republics who have the same feelings against Democrats (Pew Research Center, 2014). In line with these survey results, Iyengar and his colleagues (2012) conclude that selective

exposure to like-minded political campaign messages which have negative and biased tone toward the oppositional political party strengthens partisans' biased negativity toward the opposition (Iyengar et al., 2012). Similarly, Garrett and Tsfati (2014) note that partisan selective exposure activates negative emotions toward out-party and positive emotions toward in-party, which in turn increases the level of affective polarization.

When looking at a recent survey data in Turkey, it can easily be seen that these polarization levels are much higher in Turkish public compared to U.S. Over the three quarters of Turkish people who regard the ruling AKP as the most disliked party define this party supporters as two-faced, cruel, selfish, a threat to the nation, arrogant, and narrow minded. These high proportions of negative affections are almost the same for people who regard other oppositional parties as most disliked. For example, 70 percent of the people who regard CHP as most disliked and 83 percent who regard HDP as most disliked believe that the supporters of these parties are a threat to the nation (Institutional Social Responsibility Organisation, 2016).

The second dimension of affective polarization, which is social distance from the opposed party is generally measured by people's attitudes toward out-party marriages. A study showed that nearly 20 percent of the people that are either Democrat or Conservative feel upset if their son or daughter marry someone from the opposition party (YouGov, 2008). This affective polarization level is very close compared to Great Britain, with 19 percent of people who are Labour, and 10 percent who are conservative feel very or somewhat upset from this out-party marriage.

Strikingly, a recent survey data in Turkey shows that the affective polarization in Turkey is at greater levels compared to U.S. and U.K. when



measured based on social distance to opposed party. Political Polarization survey (2016) carried out in 2015 demonstrated that 80 percent of the people who regard the ruling AKP as the least favorable/disliked party, don't want their children to marry someone who is supporter of AKP. This proportion is also very high for people who regard oppositional parties CHP (80 percent), HDP (87 percent) and MHP (74 percent) as the most disliked party. On the other hand, above 70 percent of all political party supporters say they don't want to be neighbors with people who support their most disliked party (Institutional Social Responsibility Organisation, 2016). These high levels of affective polarization show how deep is the political and ideological division among Turkish people, especially when compared to U.S. and UK.

Moreover, another survey conducted by Bilgesam Research Company (2014) reveals that this polarization is much deeper in partisan and ideological lines when compared to ethnicity. According to the survey, only 24 percent of the Turks say they don't want to marry a Kurd, while only 3.3 percent of the Kurds say they don't want to marry a Turk. When it comes to politics, this proportions increases dramatically. 67 percent of people who support MHP, which is known as Turkish nationalist and opponent of pro-Kurdish HDP say they don't want to marry a supporter of HDP. Similarly, 37 percent of people who support pro-Kurdish HDP refuse a marriage with a supporter of Turkish nationalist MHP.

Furthermore, the same survey documents that 42 percent of CHP-supporters and 50 percent of leftists (socialists, Marxists and communists) say they don't want to marry a pro-AKP person and 69 percent and 73 percent of them respectively say they don't want a pro-AKP president. Similarly, 18 percent of AKP-supporters, and 26 percent of religious-

conservatives say they don't want to marry a pro-CHP person; while 45 percent and 53 percent of them respectively say they don't want a pro-CHP president (Akyürek & Koydemir, 2014). This survey shows that, rather than an ethnic polarization, Turkish people is deeply polarized based on partisanship and left-right ideologies.

### **3.3. Effects of Selective Exposure on Political Polarization**

The literature about selective exposure presented above clearly associates partisanship with selective exposure. Then, what are the consequences of partisan selective exposure? While there might be many other outcomes, scientists significantly focus on the effects of partisan selective exposure on political polarization. In many studies, they argue the negative effects of politically like-minded media exposure on people who have greater interest and engagement in politics. The more people reinforce their political attitudes through partisan news consumption, the greater their political polarization. Therefore, higher levels of partisan media consumption are associated with greater polarization.

These platforms might be harmful for democratic deliberation, as they promote greater selective exposure to like-minded political views, which in turn reinforce existing political attitudes, lead to political polarization, and prevent a deliberative democratic discussion (see e.g., McPherson, Smith-Lovin et al. 2001, Kelly, Fisher et al. 2005, Sunstein 2007, Zhang, Johnson et al. 2010). Sunstein is the most prominent scholar of this line of thought, who argues that Internet use would lead to politically-enclaved communication cliques, which are internally homogeneous and mutually polarized (Sunstein, 2007).

There are some empirical findings that strengthen Sunstein's theoretical claims. Selective and biased exposure to pro-attitudinal political issues are found to be related with incivility (Berry & Sobieraj, 2014), less political ambivalence and greater polarization (Lavine, Borgida, & Sullivan, 2000). In addition, pro-attitudinal selective exposure is found to be mediating the relationship between partisanship and political extremity. Similarly, Kim (2015) demonstrated that selective exposure to congenial media is correlated with higher levels of polarized attitudes both in U.S. and South Korea.

Moreover, if conducted by people who consumes only attitude-consistent information, political discussions and disagreement, which are regarded as key instruments for democratic deliberation (Diana C. Mutz, 2006), have a quite opposite effect on democracy. The findings reveal that even if people with high level of partisan selective exposure engage in public discussions with people that have an attitude-discrepant view, these public deliberations lead more polarized attitudes, rather than mitigating polarization. One possible explanation of it is that people seek out challenging views not to understand them, but to develop defensive arguments against them (Knobloch-Westerwick & Jingbo Meng, 2009).

There are some explanations about why being exposed to partisan media increases polarization. For example, when party elites go to extremes in their actions and speeches, the partisan media, which are aligned with parties and ideologies, reflect these politically extreme attitudes with a biased slant. Accordingly, the audience, who exercise partisan selective exposure to media outlets which reflect this conflicting environment with one-sided and biased political arguments, use those arguments in their interpersonal discussion networks (Katz & Lazarsfeld, 1955), which make

them develop more polarized attitudes. In the same vein, like-minded partisan news serve to reinforce political views and attitudes that already exists, which in turn leads to the creation of polarized echo chambers among groups supporting different political ideas (Iyengar & Hahn, 2009).

As internet and social media, compared to traditional media sources give more opportunities to consume politically like-minded information and filter out dissimilar views and opinions, it contributes more to political polarization. Especially social media platforms, which motivate people to communicate with like-minded others and to avoid competing views, lead to radicalization, attitude reinforcement and political extremity. Furthermore, these online settings create group identity, which in turn causes group polarization (Sunstein, 2011). According to Sunstein (2007), discussing with like-minded people as well as consuming congenial political information in online communication sources lead groups to form a shared identity. Consequently, being exposed to information within homogeneous echo chambers motivates the group members to have a more extreme position in the direction to which they were previously inclined, which posits a great risk for social peace and democracy.

Another explanation about the relationship between partisan media exposure and polarization is that the former contributes to the latter by increasing audience's familiarity with arguments and by making them to keep the political issue consistently in mind which reinforce their pre-existing political views (Gvirsman, 2014). Therefore, more selective exposure leads to more familiarity with congenial information, which in turn increases the level of polarization. Indeed, a meta-analysis demonstrated that out of 17 academic sources focusing on the relationship between partisan selective exposure and political polarization, 15 sources

found evidence about the existence of the relationship between them (Thornal, 2015). As online media platforms offer more options for consuming partisan news content, online news exposure is found to induce more affective polarization compared to offline news (i.e., TV, print newspapers, broadcast) for those with higher levels of political interest (Lelkes, Sood, & Iyengar, 2017). Indeed, when it comes to gathering information about anything, the dependency on internet is peaked compared to social and inter-personal environments. Thus, attitude formation is increasingly much more related to online media use habits. As Calhoun (1988) notes, the transformation in community structure and communications technology leads to more dependency on media as an information source about people that are not like “us”. Even if we live in the same neighborhood, we get increasingly lower inter-personal interactions with them, which makes us know them more through the glasses of media sources. Considering this dependency on media sources about attitude formation, online media consumption habits become more important in defining and evaluating “us” and “others”. In such a context, selectively exposing to attitude-consistent partisan media would lead to develop higher levels of hostile attitudes toward dissimilar groups, which will further increase polarization in public (Calhoun, 1988).

The evidence showing that attitude-consistent selective exposure reinforces political attitudes while attitude-discrepant exposure decreases the extremity of attitudes toward parties and political issues (Knobloch-Westerwick, 2012) demonstrates that there is a strong association between the amount of like-minded news consumption and the level of political polarization. Moreover, recent studies document that both selective exposure to partisan media and selective avoidance to outlets that are

slanted away from people's political views contribute equally to attitude polarization toward supported political parties and their leaders (Garrett et al., 2014).

Studies conducted outside the U.S. also find strong evidence for the relationship between partisan selective exposure and polarization. For example, Kim (2015) replicated the study of Stroud (2010) by using a national-level survey conducted in South Korea. He found that similar to the findings in U.S., greater exposure to politically like-minded news outlets lead South Korean audiences to develop more polarized attitudes. In another study, Tsfati and Chotiner (2016) measured partisan selective exposure in Israel by both survey and web-trafficking methods, and found evidence about its relationship with polarization. Likewise, a survey study conducted in 10 countries (Canada, Colombia, Greece, India, Italy, Japan, Norway, South Korea, the UK, and the U.S.) demonstrated the existing relationship between selective exposure to online news websites and perceived polarization.

On the other hand, while there is an academic debate about the direction of the relationship between selective exposure and the political polarization, recent studies find evidence that partisan selective exposure has a causal effect on political polarization. For example, in a cross-lagged analysis of a longitudinal data, Stroud (2010) found that the influence of selective exposure on political polarization was much stronger than the influence of political polarization on partisan selective exposure. In line with it, Levendusky (2013) conducted an experimental research which revealed that partisan media exposure among politically engaged people caused political polarization.

As already argued above, it is almost clear that selective exposure to partisan news outlets is associated with political polarization. What is not clear is the degree of partisan news consumption and its political effects in the whole media system. In other words, how much of the population prefers to consume only partisan media, and how much of the others prefer more centrist and mainstream news? Recent studies in U.S. show that, when allowed to choose among moderate and partisan programs, 93% of the American people preferred to tune out highly partisan cable news programs (Arceneaux & Johnson, 2013). Similarly, Garrett (2009a) demonstrated that self-exposure to partisan websites is highly exceptional. Only one internet user out of ten visits a web site which is partisan. In line with these findings, Gvirsman (2014) notes that only those who have a stronger political ideology rely more on partisan media sources and less on traditional and mainstream.

Accordingly, they argue that while these partisan media sources make already politically-interested and polarized people even more so, they are far away from turning moderate audience into extremists (Levendusky, 2014). Prior (2013) argues that greater media choice which offers more entertainment programs than political news lead nonideological and less partisan audience to tune out political news and to watch entertainment programs, which left the political sphere to strong partisans and in turn increased the impact of political polarization among the public.

Nevertheless, a relatively small audience, which have great interest, engagement and knowledge in politics might be much more influential compared to large and moderate audiences. They might spread partisan information to the large and moderate audiences through their online and interpersonal social networks. Thus, even when moderate audiences tune

out partisan media, they might be exposed to partisan messages disseminated to them indirectly, mostly via the small but highly partisan audiences. This indirect exposure to partisan messages might also cause polarization among moderate audience. Indeed, in a recent experimental study, a group of people exercised selective exposure by watching partisan news outlets, while another group only watched a-political content. Afterwards, some respondents from each of the group created a discussion group to talk about the content that they watched. The results reveal that people who didn't watch partisan messages early on and who were indirectly exposed to partisan information during the discussions were end up polarized, just like the respondents who were directly exposed to partisan media. (Druckman, Levendusky, & McLain, 2017). These empirical findings suggest that even few in number, the influence of partisan audience might be substantial to mostly-moderate mass audiences, which warns about the negative effects of selective exposure to political polarization.

On the other hand, the degree of partisan news consumption and its effect on the political attitudes might be quite different in Turkey's political media landscape. Reuters Digital News Report (2017) emphasizes that 50 percent of Turkish people who identify themselves on the left side of the political spectrum exercise selective exposure to Sözcü newspaper, which is perceived as anti-government. However, only 9 percent of people who self-identify on the right-wing reads it, which points to a high level of partisan selective exposure.

Moreover, as an insight to political polarization in Turkey, 92 percent of pro-MHP people definitely refuse to vote for HDP, and 83 of pro-HDP people say they will never vote for MHP. Similarly, 83 percent of CHP



supporters and 71 percent of AKP supporters say they will never voter for AKP and CHP respectively (Akyürek & Koydemir, 2014). These proportions point to a deep political polarization based on partisanship among Turkish people, which is a topic of this thesis and will be investigated inclusively in the following chapters.

### **3.4. Hypotheses of This Study**

Expanding on the survey results and public perceptions about selective exposure and polarization in Turkey, this thesis expects partisan news consumption to be very high and cross-cutting exposure to be very low in Turkish partisan audiences that use Twitter for reading political news. It hypothesizes that Turkish twitter users practice a high level of partisan selective exposure by following political news outlets that are consistent with their political identifications. Furthermore, these Twitter users are expected to be highly polarized in terms of following and retweeting twitter accounts (party deputies and political elites) that share their political views as well as avoiding other counter-attitudinal accounts by not following/retweeting them. Finally, by using a regression analysis with interaction terms, this thesis investigates the association between the level of partisan selective exposure and political polarization among Turkish Twitter users, which is expected to be statistically and positively significant irrespective of the party that is favored of. The main and sub-hypotheses of this thesis are explained as follows:

H1: Turkish twitter users practice a high level of partisan selective exposure by following political news outlets that share the same political views with them. Moreover, they practice a high level of selective news avoidance and very low level of cross-cutting news exposure by not following politically discrepant news outlets on Twitter.

H2: Turkish Twitter users are highly polarized in terms of following and retweeting twitter accounts that share their political views as well as avoiding other counter-attitudinal accounts by not following/retweeting them.

H3: Partisan selective exposure to politically like-minded news outlets on Twitter has a significant association with political polarization, whereas exposure to cross-cutting news outlets is related with more moderate attitudes.

H3a: Partisan selective exposure to pro-AKP news outlets has a significant association with politically polarized attitudes toward AKP.

H3b: Partisan selective exposure to pro-CHP news outlets has a significant association with politically polarized attitudes toward CHP.

H3c: Partisan selective exposure to pro-HDP news outlets has a significant association with politically polarized attitudes toward HDP.

H3d: Partisan selective exposure to pro-MHP news outlets has a significant association with politically polarized attitudes toward MHP.

Note that the last hypothesis has nothing to say about the causality or the direction of the association between partisan selective exposure and polarization. Although past studies conducted with a cross-lagged panel model (Stroud, 2010) suggest that partisan selective exposure leads to polarization, the cross-sectional Twitter data set used in this study can not establish such a directional causality. At best, it can only rely on that past research to assume that partisan selective exposure has more influence on predicting political polarization than polarization's influence on predicting partisan selective exposure (Garrett et al., 2014; see e.g., Gvirsman, 2014; see

e.g., Levendusky, 2017). Therefore, when testing their association with a regression analysis, the direction of the association is identified based on the past research.

## CHAPTER 4

### METHODOLOGY

This chapter explains the data collection, measurement, and operationalization methods that are used in this study. Chapter 4.1 explains which data is used in order to measure partisan selective exposure on Twitter, as well as which methods and operationalization strategies are used in order to perform this measurement. Chapter 4.2 clarifies the data collection, measurement and operationalization processes for creating two different types of political polarization indices, which are partisan and retweet polarization. Chapter 4.3 explains how to investigate the association between partisan selective exposure and polarization. More specifically, it illustrates what variables are used to analyze this association, how these variables are created within the Twitter database, and which method is used to investigate their statistical association. In an effort to validate the estimation of polarization and partisanship indices that are used in the analyses, Chapter 4.4 uses alternative measurement methods for these variables.

#### **4.1. Partisan Selective Exposure on Twitter**

##### **4.1.1. Conceptual Framework for the Selective Exposure Methodology**

Measuring partisan selective exposure requires capturing both political predispositions and selective exposure to congenial media at the same time (Stroud, 2010). If a Twitter user's political leaning is not known,

then it would be impossible to identify whether her media selectivity is congenial or uncongenial based on partisanship. For instance, to measure partisan selective exposure toward pro-AKP media, it is required to know in advance whether the Twitter user is identified as pro-AKP or not. If the user is in favor of the ruling AKP, then her like-minded (pro-AKP) news exposure is defined as partisan selective exposure. Otherwise, as her political views will not correspond with the political slant of the news that is being exposed, it would be defined as cross-cutting news exposure.

On the other hand, before measuring partisan selective exposure to news outlets that are slanted toward specific political parties or ideologies, each news outlet that is included into the research needs to be classified as either party/ideology-affiliated or moderate. Otherwise, for example, it would make no sense to measure selectivity of AKP-leaning audience toward news outlets whose slant toward specific political parties or ideologies are not identified.

Therefore, to investigate partisan selective exposure, some preliminary research should be conducted. First, each news outlet's slant toward political parties and ideologies should be identified. Second, each Twitter user's political predisposition and its strength (such as strong pro-AKP, weak Pro-AKP, moderate etc.) should be designated. Combining the political predispositions of the Twitter user and the consumed media source will then make sense in determining whether the exposure is partisan or cross-cutting.

Academic researchers implement some basic strategies to measure partisan selective exposure. The most common strategy is to conduct surveys. By using surveys, respondents are asked some questions that

separately measures their political predispositions and their level of selective exposure to media that match their political dispositions.

To measure ideological partisanship, respondents are generally asked to define themselves as very/extremely conservative, conservative, moderate, liberal, or very/extremely liberal. Similarly, to measure political partisanship, respondents are asked to define themselves as strong Republican, not very strong Republican/close to the Republican Party, not leaning toward either party, not very strong Democrat/close to the Democratic Party, or strong Democrat. In U.S., as survey results reveal that there is a statistically significant correlation between strength of political partisanship and strength of ideology, these two measures are generally combined to create a single variable indicating political leaning (see e.g., Stroud, 2008).

To measure selectivity toward attitude-consistent media sources in surveys, two approaches are used. In “actual measures” approach, the respondents are asked to self-report their most frequently consumed news outlets, the slant of which are identified in advance by the researcher. In the “perception measure” approach, respondents are asked to self-report their most frequently consumed news outlets as well as their perceptions about whether the slant of these outlets are congenial or uncongenial with their political leanings (Yonghwan Kim, 2015).

In actual measures approach, respondents are generally asked which news source they consume most often (Stroud, 2010) or most recently (Gentzkow & Shapiro, 2011). Followingly, if the political orientation of the outlet that is read most often matches with the political orientation of the respondent, then they are assumed to have a partisan selective exposure.

On the other hand, if the political orientation between news outlets and respondents doesn't match, then they are assumed to lack a partisan selective exposure (see e.g., Garrett et al., 2014). To illustrate, reading a pro-AKP newspaper by a Pro-AKP respondent means partisan selective exposure, whereas reading a pro-AKP newspaper by a Pro-CHP respondent points to counter-party (cross-cutting) exposure.

As a second strategy, some surveys ask respondents to identify how frequently they are exposed to each news outlet *-that is placed to a certain position in advance by the researchers in the political spectrum-* on a scale, mostly ranging from 1=never, to 7=very frequently (e.g., Yonghwan Kim, 2015). On this strategy, partisan selective exposure is measured by averaging the frequency score of the outlets which corresponds with participants' political predispositions.

It should be noted that partisan selective exposure cannot be attributed to moderate people who are non-partisan, as they don't possess a political leaning to be associated with any news outlet. Although they also have media consumption preferences, whether this media selectivity matches with their political predispositions or not can not be identified without knowing their political party leanings. Therefore, non-partisans are omitted from the analyses while investigating partisan selective exposure.

Another strategy is to carry out laboratory-based experimental studies. In experiments, respondents with diverse political leanings are invited to choose one of the political media source (political web site, news article, a TV program, a brochure, a statement etc.) including contradictory and neutral political views. Which content/source is selected by which respondent is a way of measuring selectivity. The hypothesis for these

experiments is, if selective exposure exists, given the opportunity to select a news content, people tend to choose the one which is congenial. In many of these laboratory-based experiments, respondents were found to exercise selective exposure to media sources which is congenial to their political predispositions (e.g., Taber & Lodge, 2006).

As a fourth strategy, automatic Internet tracking data is used to measure online selective exposure. For example, in U.S., comScore company installs to some internet users' computers a software to monitor their web-browsing and media consumption behavior, which enables scholars to investigate their selectivity toward partisan media. As this data doesn't involve the political leanings of the audiences whose web-browsing is tracked, this data is combined with a separate survey which measures these audiences' political leanings (see e.g., Gentzkow & Shapiro, 2011).

Prior (2009) argues that, self-reported exposure to media outlets in surveys are not very accurate and shown to have low validity and reliability, as many respondents fail to remember the extent of exposure as well as forgetting, exaggerating, and underestimating it. He also suggests that future search on selective exposure should avoid self-reported news consumption data and rely on automatic tracking data which monitors the extent of media consumption without any self-bias (Markus Prior, 2013b).

Expanding on these notions, this thesis investigates the extent of selective news exposure by using an original online data. As such, this thesis tracks the twitter data of all the Turkish Twitter population who follows the accounts of political news outlets as well as deputies of political parties on Twitter.



With social media platforms becoming more common for people seeking out news (Newman et al., 2017), even print and legacy news outlets began to publish their news reports on these platforms. Moreover, these platforms encouraged the audience who are seeking-information to move from traditional media sources such as TVs and newspapers to online mediums such as Twitter. Therefore, following news on Twitter is a new opportunity to investigate media consumption patterns of a society (An, Cha, Gummadi, Crowcroft, & Quercia, 2012) as well as to investigate diversity of selective exposure in social media (Himmelboim et al., 2013).

Based on the 2017 Reuters Digital News report (2017) demonstrating that 61% of Turkish Twitter population uses Twitter for reading news, this thesis suggests that Twitter is a very suitable platform to monitor attitude-consistent (partisan) and cross-cutting (attitude-discrepant) news exposure.

#### **4.1.2. Data**

Twitter is a very appropriate platform for an academic study as it contains huge volume of personal and relational information. While tweets of Twitter users imply their political orientations; their followers and followees point to their social and political network as well as whether this network is politically homogeneous or heterogeneous. Moreover, this information is mostly available to the public and researchers. As being the most common and widespread microblogging website, Twitter increasingly overflows with millions of user data including screen names, statues, profile images, locations, followers, followees, tweets, retweets, replies, mentions, hashtags that is associated with each Twitter user. Therefore, in order to collect big data for conducting researches, it is challenging to manually track users' activities on Twitter. Instead, for

helping researchers for their analyses, Twitter offers two separate application program interface (API), one of which is used in the analyses of this thesis. This thesis uses Twitter’s REST API, -which provides permission (with a rate limit) to collect data from any user’s account upon request-, to scrape data of Twitter users who follow Turkish political news outlets and political party deputies. This data is requested from Twitter by using a programming language, Python, with the help of a Twitter module created by Django, which is a Python web framework that simplifies developers’ projects.

To investigate selective exposure to news outlets on Twitter, first, political news outlets that have an account on Twitter and that report nation-wide (instead of local or regional) news are searched<sup>1</sup>. To facilitate the further analyses, outlets that are followed by less than 10.000 Twitter users are excluded. Resultingly, 53 news outlets that have a political news content have been identified. Of those outlets, 26 of them are the twitter accounts of print and legacy newspapers, and 27 of them are digital-born and digital-only outlets that don’t have a print version. Table 1 shows the descriptive information about these news outlets.

**Table 1**

*Descriptive Information about Turkish Political News Outlets on Twitter*

No	Twitter Account	Name	Label	Type	# Followers
1	Aksam	Akşam	AKS	Print	875045
2	AydinlikGazete	Aydınlık	AYD	Print	299400
3	BirGun_Gazetesi	Birgün	BIRG	Print	932892
4	cumhuriyetgzt	Cumhuriyet	CUM	Print	2140923

<sup>1</sup> The lists of digital news outlets are investigated through these web-sites: <http://www.medyajans.com/haber-siteleri>, <http://www.medyafaresi.com/haber/turkiyede-en-cok-tiklanan-ilk-100-haber-sitesi/103882>, and <https://www.gazeteoku.com/internet-medyasi-siteleri.html>

**Table 1 (Continued)**

5	dirilispostasi	Diriliş Postası	DRL	Print	56872
6	evrenselgzt	Evrensel	EVR	Print	380355
7	gunes_gazetesi	Güneş	GUN	Print	348804
8	Haberturk	Habertürk	HBTR	Print	3831158
9	Hurriyet	Hürriyet	HUR	Print	4204186
10	KararHaber	Karar	KRR	Print	189345
11	milatgazete	Milat	MLT	Print	90927
12	milligazetecom	Milli Gazete	ML_GZ	Print	104830
13	milliyet	Milliyet	MILL	Print	2484259
14	gazeteortadogu	Ortadoğu	ORTD	Print	80885
15	Sabah	Sabah	SBH	Print	1827179
16	gazetesozcu	Sözcü	SOZC	Print	1386967
17	stargazete	Star	STR	Print	1114405
18	takvim	Takvim	TKV	Print	120882
19	turkiyegazetesi	Türkiye	TRK	Print	213995
20	yeniakit	Yeni Akit	Y_AK	Print	145819
21	yeniasya	Yeni Asya	Y_AS	Print	36192
22	Gazete_Yenicag	Yeniçağ	Y_CG	Print	45346
23	yenisafak	Yeni Şafak	Y_SF	Print	720390
24	yurtgazetesi	Yurt	YRT	Print	191751
25	2023Gazete	Gazete 2023	2023	Digital-Only	14370
26	abcgazete	ABC	abc	Digital-Only	96755
27	artigercek	Artı Gerçek	artı	Digital-Only	52339
28	BeyazGazete	Beyaz Gazete	byz	Digital-Only	42656
29	bianet_org	Bianet	bia	Digital-Only	238448
30	DikenComTr	Diken	dkn	Digital-Only	701190
31	dokuz8haber	Dokuz8 Haber	dkz8	Digital-Only	93710
32	ensonhaber	Ensonhaber	enso	Digital-Only	418673
33	EtikHaber	Etikhaber	etik	Digital-Only	18581
34	gazetebirlik	Yeni Birlik	ynbr	Digital-Only	50892
35	GazetecilerCom	Gazeteciler	gztc	Digital-Only	54965
36	gazeteduvar	Gazete Duvar	duvr	Digital-Only	108219
37	gazeteistiklal	İstiklal	istk	Digital-Only	1623117
38	Gazeteport_com	Gazeteport	gztp	Digital-Only	42284
39	gercekgundem	Gerçek Gündem	grck	Digital-Only	128348
40	GrihatHaber	Grihat	gri	Digital-Only	54102
41	Haber7	Haber7	hb7	Digital-Only	869290
42	Haberler	Haberler	hbrl	Digital-Only	108678
43	habervaktim	Habervaktim	hbvk	Digital-Only	15510
44	internethaber	Internethaber	inth	Digital-Only	209302

**Table 1 (Continued)**

45	medyafaresi	Medyafaresi	m_fr	Digital-Only	128928
46	medyaradar	Medyaradar	m_rd	Digital-Only	91337
47	odatv	Odatv	oda	Digital-Only	882691
48	sivilmedyahaber	Sivil Medya	svl	Digital-Only	103703
49	solhaberportali	Sol Haber Portalı	sol	Digital-Only	626602
50	t24comtr	T24	t24	Digital-Only	971274
51	turktimeCom	Türk Time	turk	Digital-Only	14842
52	ulkucumedyacom	Ülkücü Medya	ulkc	Digital-Only	478741
53	YonHaber	Yön Haber	yon	Digital-Only	22679

After identifying Twitter accounts of news outlets, each news outlet's complete list of followers is collected from Twitter and stored to a database. The data collection on Twitter took place in January of 2018. In sum, 11.418.240 distinct Twitter users who have a total of 30.085.033 following links<sup>2</sup> to at least one news outlet are transferred into the database.

As explained, this Twitter data is collected to measure selective news exposure. To identify partisan selective exposure and its relationship with political polarization, a second Twitter data is collected. More specifically, the Twitter accounts of deputies of four major political parties that have a seat in Turkish parliament (AKP, CHP, MHP, and HDP) as well as official accounts of these parties are searched. The deputies whose twitter accounts have not been active longer than one month are not included into the sample. Within this context, 493 party deputies (AKP = 285, CHP = 126, HDP = 49, MHP = 33) and 4 party official accounts are gathered. In sum, 16.520.139 distinct Twitter users who have a total of 78.890.721 following links to at least one political party or deputy account are transferred into the database.

<sup>2</sup> As Twitter users might follow multiple outlets or party deputies, "following links" refer to the number of accounts that are followed on Twitter. A Twitter user who follows 10 different news outlets will have a total of 10 following links in the database. The same user who also follows 5 different political party deputies as well as 1 party official account will have a total of 16 (10+5+1) following links in the database.

When the two data sets are merged, the Twitter database composed of 109.002.588 following links among 21.418.717 distinct Twitter users who followed at least one news outlet and at least one political account.

As this thesis focuses on partisan selective exposure and its relationship with polarization, Twitter users who followed less than 2 news outlets and less than two party/deputy accounts are excluded. Resultingly, the remaining data set reduced to 48.316.548 following links to at least two news outlets and two political parties among 2.790.339 distinct Twitter users. These users and their following links comprise the sample for the following analyses of this study.

### **4.1.3. Measurement**

#### **4.1.3.1. Measuring News Outlets' Partisan Leanings**

After collecting follower lists of 53 news outlet accounts on Twitter, the second step for measuring partisan selective exposure involves identifying the partisan leanings of each outlet. Although there are some various methods for classifying each outlet's association with certain political parties and ideologies, this thesis uses graph theory and Social Network Analysis (SNA) to separate news outlets into ideologically diverse clusters. More specifically, it uses bipartite relation analysis to create clusters of media outlets that are internally similar and externally dissimilar.

The logic behind this analysis hinges upon the "homophily principle", which suggests that people are more likely to contact with similar people compared to dissimilar people. Sunstein (2011) argues that because of homophily phenomenon, people who share same attitudes tend

to seek out one another which results in the creation of social networks among like-minded individuals. As a basic organizing principle, homophily principle claims that similarity of two objects in a network (such as knowing about the same person, sitting on the same chair, sharing the same attitudes and values), increases the probability of a positive tie among them and accordingly breeds fellowship (McPherson, Smith-Lovin, & Cook, 2001). For example, Krebs (2004) linked people to each other who purchased same political books on amazon.com and demonstrated that conservatives and liberals were segregated into diverse clusters in terms of purchasing and recommending certain political books on Amazon. Similarly, Barberá et al. (2016) documented that political location of news outlets can be inferred by analyzing their co-followership on Twitter. Prior (2007) noted that the overlap between audiences who watches the same Tv channels provides strong signs for selective exposure to congenial media. Barberá et al. (2015) estimated the ideological preferences of 3.8 million Twitter followers simply by observing their “following” connections to political accounts. They demonstrated that political ideologies of Twitter users can be inferred on the basis of their following links to politically homogeneous networks, as these links are governed by homophily principle and indicator of political similarity (Barberá et al., 2015). Lee and Hahn (2017) grouped Korean National Assembly members (party deputies) into political clusters based on their co-followers on Twitter. By using a similarity index which is similar to that of this thesis, they found that the co-subscription degree of each pair of party deputies on Twitter successfully infer their political positions in the Korean National Assembly.

Followingly, this thesis suggests that similarity of two news outlets based on co-followership on Twitter refers to the political/ideological

proximity of these outlets, whereas dissimilarity of two outlets by being followed by separate groups of people refers to the political/ideological distance between them.

In Social Network Analysis (SNA) terminology, two-mode or bipartite data refers to two disjoint sets, where members of one set have links to members of other set but not to members of the same set. While there is no identified links within members of each set, these members can be linked to each other by investigating the extent of joint links among members of one set toward members of other set.

Two-mode data generally appears in networks including two types of objects, which are playing separate roles. For linking those two separate sets of objects, co-occurrence frequency analysis is conducted. For example, considering one set of items involves consumers of books, and other set of items involves books that are purchased by those consumers, there is a connection between consumer  $i$  and consumer  $j$  if and only if the consumer  $i$  and consumer  $j$  purchases the same book (Fouss, Saerens, & Shimbo, 2016). Commonality of connections between two-mode data enable the analysis of both types of data sets. Following the same example above, there is also a connection between book  $i$  and book  $j$ , if and only if the book  $i$  and book  $j$  are purchased by the same consumer(s).

Accordingly, Twitter network data in this thesis consists of two disjoint sets of entities; news outlets ( $n=53$ ) and followers of these outlets ( $n=2.790.339$ ). While one mode refers to the set of news outlets among which there are no identified ties, the other mode refers to the set of followers which are also not connected to any other in the network data. Although each of these data sets are unconnected, the share of links from a certain

follower to multiple outlets imply a connectivity between these outlets. Therefore, more users following the same two outlets refers to more proximity between these outlets. On the contrary, less followers sharing the same following links to any two outlets refer to less proximity between them.

In political communication literature, Groseclose and Milyo (2005) used a similar method to categorize media outlets according to their political orientations. They investigated the share of news outlets and political party legislators in terms of their frequency of references to the same think tank organizations. They hypothesized that the higher the frequency of a news outlet and a legislator's joint reference to the same think tank, the closer the outlet is to the political ideology represented by that legislator. While their study and method is much appreciated in terms of not including any subjective judgements about the slant of the news content, they are criticized by not taking into consideration the negative slant in the news coverage or Congressional legislator speech toward think-tanks (Markus Prior, 2013a).

Expanding upon the study of Groseclose and Milyo (2005), Jisun An et al. (2012) investigated the ideological distance of news outlets on Twitter based on their followers' co-subscription similarity. More specifically, they collected 7 million Twitter users who followed 24 major news outlets that publish news in U.S. Afterwards, they created a distance model based on the similarity and dissimilarity of co-subscribers of each outlet, which places each outlet to a position in the U.S. political spectrum. While very similar to the strategy of this thesis, the difference of the methods is that Jisun An et al. (2012) used the ideological positions of four news outlets (Fox, GMA, Today Show, and NPR News), which were identified by Gresco



and Milyo (2005) in advance, as Landmarks. They proceeded their analysis by identifying other news outlets' ideological position based on their proximity to the landmarks of those four outlets, whose political leanings are already known and included to the analysis beforehand.

James Cook (2014) demonstrates that the amount of shared mentions by various Twitter users toward two legislators of Maine State (U.S.) on Twitter indicates their degree of political similarity. He argues that the more two legislators are co-mentioned by Twitter users, the more their political similarity.

Similarly, Barberá and Sood (2016) estimated the ideological proximity of news outlets, journalists and political party legislators based on their frequency of co-followers on Twitter. Moreover, they compared the location of each outlet in ideological space with those of congressmen and legislators. They found that (1) each outlets' position in ideological scale is consistent with previous ideological categorization of those outlets, (2) the correspondence of outlet and political actor dimensions in the latent scale shows a high validity of the measure, (3) the latent dimension created by co-followership of Twitter users reflects political ideology, and (4) outlets' relative positions in political spectrum is highly consistent with the public perceptions (Pablo Barberá & Gaurav Sood, 2016).

In another study, Jisun An et al. (2011) measured similarity of 80 different media sources including TV's, magazines, news outlets and journalists based on their 14 million followers' co-subscription patterns on Twitter. By assuming that a Twitter user follows news outlets that match their political views, they labelled media sources that have many followers in common as "closely related". They defined distance/closeness of each

pair of media sources (such as A and B) as the probability that a random follower of A also follows B. They found a strong correlation between the closeness values of media sources created by the bipartite graph analysis and ADA (Americans for Democratic Action) score developed by Groseclose and Milyo (2005), which is an accepted method for measuring media bias in U.S. and requires advanced text classification (An et al., 2011).

Expanding on the theoretical backgrounds and methods of these studies, this thesis measures the political proximity between news outlet by investigating the extent of their similarity based on their co-subscription (co-followership).

#### **4.1.3.1.1. Operationalization (Political Proximity and Clustering of News Outlets)**

In social networks, there are some similarity index methods for predicting the strength of links between objects which are not directly connected, and which are members of disjoint data sets. Most common of these indices include Common Neighbours, Jaccard's Index, Adamic/Adar Index, Cosine Similarity Index, Hub Promoted/Depressed Index and Chi-Square Similarity Index. These similarity-based link prediction algorithms compute the degree of similarity between each pair of object in a set based on their common neighbors that are members of other set (Srilatha, Pulipati & Manjula, Ramakrishnan, 2016). By investigating the similarity of disconnected nodes based on their common links to other nodes, these algorithms aim to reveal the connection between those nodes that are missing in the network structure.

The literature shows that some prediction methods provide better performance in certain network structures, but they can be powerless for

some other networks. Accordingly, there is not a single method that could be the best and most accurate predictor of similarity for all kinds of networks (Gao, Musial, Cooper, & Tsoka, 2015).

For example, common neighbours method assumes that intersection between common neighbors of two nodes shows the strength of relationship between them. However, this prediction can be erroneous if the nodes have disproportionate amount of links. To illustrate, consider 3 news outlets, Gazete2023, etikhaber, and Hurriyet, whose total number of followers on Twitter are 11.116, 16.522 and 1.564.832 respectively<sup>3</sup>. The common neighbour intersection between Gazete2023 and etikhaber (the number of followers who follow both news outlets), which shows their similarity index, is 3321. On the other hand, the similarity index between Gazete2023 and Hurriyet based on common neighbours method is 6782, which is two times bigger than the previous index. When common neighbours method is used as a similarity index, it would be concluded that Gazete2023 is two times closer to Hurriyet newspaper than etikhaber. However, when considering those outlet's number of followers, with Gazete2023 and etikhaber have less than 20.000 followers and with Hurriyet more than one million, it should be expected that Gazete2023 and etikhaber would be much closer to each other, as a large portion of their followers follow each other reciprocally. For example, while 20% of etikhaber's followers also follow Gazete2023, only 0,4% of Hurriyet's followers also follow Gazete2023. Apparently, this index is clearly not suitable for

---

<sup>3</sup> These numbers represent the followers who follow at least 2 news outlet AND at least two political party/deputy on Twitter. The original follower numbers of these outlets 14.400, 18.600 and 4.204.000 respectively.

measuring similarity of news outlets which have very different numbers of followers.

Therefore, this thesis uses Chi Square similarity measure, which is based on Common Neighbors method, and which is a standard measure for association between two categorical variables, as a better and more accurate method for measuring similarity between news outlets. To illustrate, while the similarity index based on the common neighbours measure between Gazete2023 - etikhaber is 2194 and the index for Gazete2023 - Hurriyet is 5172, the corresponding values in chi-square test of association is 162.595 and 100 respectively, which give much more accurate and logical results for news outlets' network data. Moreover, this measure is used in some other studies to measure the degree of similarity between objects. For example, Ibrahimov and his colleagues (2002) measured the similarity between documents based on word co-occurrence by using Chi Square similarity measure. They compared the results with that of other link-prediction methods and concluded that Chi-Square similarity measure produces higher or at least compatible accuracy and robustness compared with Cosine Index and Jaccard's Index. Similarly, Costa and his colleagues (2015) measured the degree of document similarity by measuring the chi-square values of each document-pair based on their common contents.

A symbolic 2\*2 contingency table and the calculation of chi-square measure for two categorical variables in it is illustrated in Table 2.

**Table 2:**

*Formula of Chi-Square Measure for 2\*2 Contingency Tables*

		News Outlet (A)		
		Yes	No	Sum
News Outlet (B)	Yes	a	b	a+b
	No	c	d	c+d
	Sum	a+c	b+d	n

$$\chi^2 = \frac{n(ad - bc)^2}{(a + c)(b + d)(a + b)(c + d)}$$

Based on this formula, each news outlet is regarded as a categorical variable in terms of whether being followed by another outlet (Yes) or not (No). The letters in Table-1 can be explained as follows:

- “a” refers to the number of Twitter users who both follow News Outlet (A) and News Outlet (B),
- “b” refers to the number of Twitter users who follow News Outlet (B) but don’t follow News Outlet (A),
- “c” refers to the number of Twitter users who follow News Outlet (A) but don’t follow News Outlet (B),
- “d” refers to the number of Twitter users who follow neither News Outlet (A) nor News Outlet (B).

Followingly, the similarity index of each pair of news outlet is calculated by using Chi-square formula. Table 3 shows the chi-square association scores of Gazete2023, etikhaber and Hurriyet, which was illustrated as an example above.

**Table 3**

*Computing Chi-Square Similarity between Gazete2023-Etikhaber and Gazete203-Hurriyet Newspapers*

		2023Gazete				Sum
		Yes		No		
EtikHaber		Observed	Expected	Observed	Expected	
	Yes	3321	65	13201	16456	16522
	No	7795	11050	2766022	2762766	2773817
	Sum	11116		2779223		2790339

$$\chi^2 = 162.595 \text{ Phi} = 0.24 \text{ } p < .0001$$

		2023Gazete				Sum
		Yes		No		
Hurriyet		Observed	Expected	Observed	Expected	
	Yes	6782	6258	1564309	1564832	1571091
	No	4334	4857	1214914	1214390	1219248
	Sum	11116		2779223		2790339

$$\chi^2 = 100 \text{ Phi} = 0.01 \text{ } p < .0001$$

When looking at Table 3, we see that, of the 16522 Twitter users who followed etikhaber.com on Twitter, 3321 of them also follow Gazete2023. However, statistical probability estimation of this value is, 65, which is far below the observed value, and which indicates that Etikhaber and 2023Gazete's Twitter audience overlap is much greater than the statistically expected overlap between these outlets. Therefore, this great overlap points to a close similarity based on their Twitter co-subscribers and hence strong association between them ( $\chi^2 = 162.595$ ). On the other hand, of the 1.571.091 Twitter users who followed Hurriyet.com on Twitter, only 6782 of them also follow Gazete2023. Moreover, statistically expected value of this co-subscription is very close to the observed value, which is 6258<sup>4</sup>.

<sup>4</sup> Probability estimates and significance values are calculated via <http://vassarstats.net/tab2x2.html>

Accordingly, these values indicate that association between Hurriyet and Gazete2023 based on their Twitter co-subscribers are very weak ( $\chi^2=100$ ).

While chi-square is a robust method for measuring association between categorical variables, the size of the chi-square statistic might not provide a reliable outcome to investigate strength of the association, especially if the sample sizes of the 2\*2 contingency tables are quite different. For example, consider two pairs of outlets, A-B and C-D, whose similarity index we would like to know. If those pairs have similar number of followers (such as A=11.000 and B=1.500.000; C= 1.500.000and D=11.000), then it would be possible to assume that larger chi-square values refer to stronger statistical relationship for the corresponding pairs. However, when the follower number of outlet pairs differ (such as A=11.000 and B=15.000; C= 1.500.000 and D=1.100.000), their chi-square values would be an incorrect indicator to compare each pair's strength of association. One of the best ways to overcome this disproportionate sample size problem is to adjust chi-square values by using Phi measure, which adjusts the chi-square statistic by the sample size (Gingrich, 1992). Phi is calculated as;

$$\phi = \sqrt{\frac{\chi^2}{n}}$$

Where  $\chi^2$  refers to chi-square value and  $n$  refers to the sample size (i.e., total number of followers of the two outlets in a pair). Accordingly, for adjusting the chi-square statistic by the sample size, each chi-square similarity measure between paired outlets are first divided by their total number of follower size and then the square root is taken, which gives the Phi values of each pair, ranging from 0 (no statistical association) to 1 (very high association).

After identifying the standardized Phi values, these values are transferred into a SNA application, PAJEK (Batagelj & Mrvar, 1998), which is a useful tool for analyzing social networks and for partitioning the network into sub-networks based on their connection patterns. To create separate media clusters within which outlets are connected to each other with higher Phi values, Louvain Method (Blondel, Guillaume, Lambiotte, & Lefebvre, 2008), a powerful community detection algorithm for large networks are used. This algorithm uses the line values (Phi values in our study) among each pair of nodes to partition them into meaningful clusters.

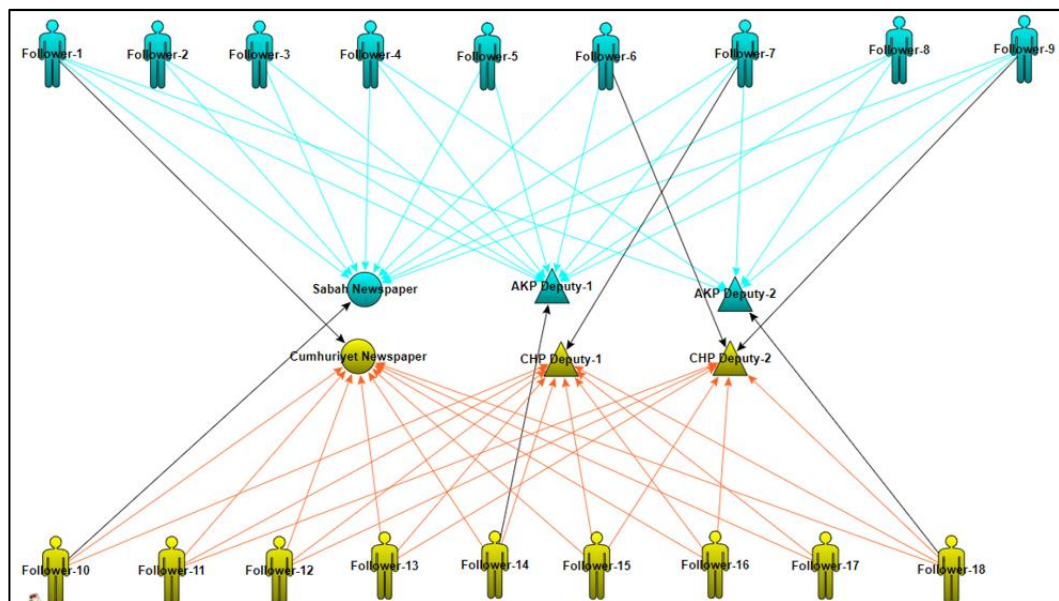
It should be noted that Louvain Clustering algorithm includes the “resolution parameter”, which enables to control the size and number of communities in a network (Mrvar, Andrej & Batagelj, Vladimir, 2018). While resolution parameter ( $r=1$ ) means standard Louvain method, higher resolutions produce larger numbers of clusters. These higher parameters enable to uncover more specific clusters. For example, a clustering analysis with a resolution parameter “ $r=1$ ” could gather many outlets that are ideologically right oriented. However there are many sub-groups of media outlets which are ideologically right but represent different right-wing political parties. Higher resolutions would reveal more specific and party-associated media clusters based on their co-followership. Therefore, in this thesis, three different resolution parameters ( $r=1$ ,  $r=1.3$  and  $r=1.5$ ) are used to investigate different size of media clusters, which gave three separate but complementary networks, each of which will be defined as “selective exposure network” throughout this thesis.

On the other hand, to verify and strengthen the clustering method for “selective exposure networks”, another strategy is also exercised. More specifically, a second network is created based on phi values between each



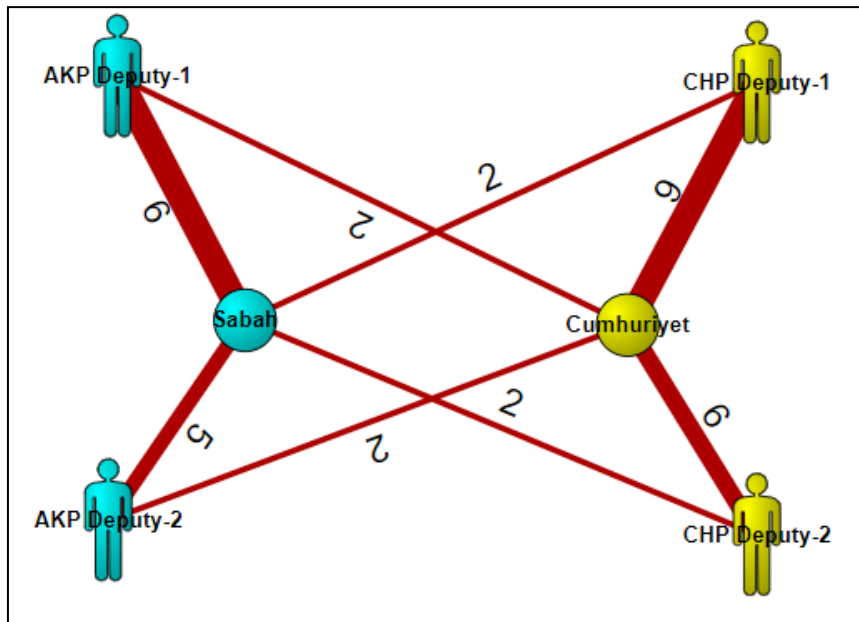
pair of news outlet and party/deputy on Twitter. As this second network uses the amount of co-followers overlap between outlets and political parties, this network and its complementary networks with higher resolutions ( $r=1.3$  and  $r=1.5$ ) are called “partisan selective exposure network”. In brief, while selective exposure network is created based on line values between each pair of news outlets, partisan selective exposure network is created based on line values between outlets and party deputies.

Therefore, for creating “partisan selective exposure network”, where a user followed both a news outlet and a party account or party deputy, a link is created between that outlet and political party. Afterwards, those link values are used for measuring chi-square and followingly Phi values among each pair of outlet-party. Figure 1 illustrates the logic behind this strategy by giving a simple example.



**Figure 1.** Illustration of the Logic Behind the Partisan Selective Exposure Network

Figure 1 shows an example of Twitter network which consists of following links from 18 Twitter users to accounts of two news outlets (Sabah, Cumhuriyet) and to accounts of four political party deputies (AKP Deputy -1, AKP Deputy -2, CHP Deputy -1, CHP Deputy -2). As seen in the graph, the network consists of two disjoint data sets with a set of followers and a set of followees (outlets and deputies). While there is no connectivity within each set, bipartite relation analysis enables to link newspapers and political parties based on their common neighbours (co-followers). Figure 2 illustrates the transformed relationship between news outlets and political parties based on their co-followers.



**Figure 2.** The Illustration of Transformed Relationship between News Outlets and Political Parties Based on their Co-followers.

As seen in Figure 2, line values between news outlets and political party deputies are created by their overlap amount of co-followers on Twitter. For example, while there are 9 users (Follower 1...9) who both follow Sabah and AKP-Deputy-1, there are only two followers (Follower 7 and Follower 10) who both follow Sabah and CHP Deputy-1, and again two

followers (Follower 6 and 9) who both follow Sabah and CHP Deputy-2. These co-follower numbers imply strengths of association between outlets and parties, where thicker lines with higher values represent stronger and smaller values represent weaker relationships. Based on this methodology, each news outlet's proximity (Phi value) to political party account or a deputy account is calculated. Note that the partisan selective exposure network consists of links between 497 political entities (493 deputies and 4 official party accounts) and 53 news outlets. Therefore, these links are used to associate each outlet with a particular political party.

The aim of this "partisan selective exposure" network is mostly to clarify the political positions of outlets that seem unclear in previous "selective exposure network". Moreover, it aims to identify political label of each media cluster in selective exposure network based on their corresponding positions in partisan selectivity network. As this network enables to partition news outlets along with their associated political party deputies into clusters, distinct party deputies that are clustered within each group of news outlet would reveal the party-associations of those media groups. For example, a clustering analysis which partitions a group of news outlets together with AKP-deputies and another group of news outlet together with CHP-deputies would reveal the party association of those media groups as being pro-AKP and pro-CHP respectively. Lastly, partisan selective exposure network is used as a validity verification method by investigating the statistical correlation between cluster positions of outlets in each network. Table 4 shows the clustering positions of each news outlet in 6 different networks, where the first three networks refer to "selective exposure network" and other three networks refer to "partisan selective exposure network".

**Table 4:***Clustering Positions of 53 Outlets in Selective Exposure (S.E.) and Partisan S.E Networks with Different Resolutions*

No	Account	Clusters in S.E. Network			Clusters in Partisan S.E. Network			Partisan Clustering
		r=1, NC=3	r=1.3, NC=7	r=1.5, NC=8	r=1, NC=4	r=1.3, NC=9	r=1.5, NC=9	
1	Aksam	Right	AKP	Right-Leaning	AKP	AKP	AKP	AKP
2	AydinlikGazete	Left	Left-1	CHP	CHP/HDP	CHP/HDP	CHP	CHP
3	BirGun_Gazetesi	Left	Left-1	HDP	CHP/HDP	CHP/HDP	HDP	HDP
4	cumhuriyetgzt	Left	Left-1	CHP	CHP/HDP	CHP/HDP	CHP	CHP
5	dirilispostasi	Right	AKP	AKP	AKP	AKP	AKP	AKP
6	evrenselgzt	Left	Left-1	HDP	CHP/HDP	CHP/HDP	HDP	HDP
7	gunes_gazetesi	Right	AKP	AKP	AKP	Undefined	Right-Leaning	AKP-Leaning
8	Haberturk	Right	Center	Right-Leaning	AKP	AKP	AKP	AKP-Leaning
9	Hurriyet	Right	Center	Right-Leaning	Undefined	Undefined	Right-Leaning	Centrist
10	KararHaber	Right	AKP Leaning	AKP Leaning	AKP	AKP	AKP-Leaning	AKP-Leaning
11	milatgazete	Right	MHP	AKP	AKP	AKP	AKP	AKP
12	milligazetecom	Right	AKP Leaning	AKP Leaning	AKP	AKP	AKP-Leaning	AKP-Leaning
13	milliyet	Right	Center	Right-Leaning	AKP	AKP	Right-Leaning	AKP-Leaning
14	gazeteortadogu	Center	MHP	MHP	MHP	MHP	MHP	MHP
15	Sabah	Right	AKP	Right-Leaning	AKP	AKP	AKP	AKP
16	gazetesozcu	Left	Left-1	CHP	CHP/HDP	CHP/HDP	CHP	CHP
17	stargazete	Right	AKP	Right-Leaning	AKP	AKP	AKP	AKP
18	takvim	Right	AKP	AKP	AKP	AKP	AKP	AKP
19	turkiyegazetesi	Right	AKP	AKP	AKP	AKP	AKP	AKP
20	yeniakit	Right	AKP	AKP	AKP	AKP	AKP	AKP
21	yeniasya	Left	Left-2	Left	CHP/HDP	CHP/HDP	CHP	CHP

**Table 4 (Continued)**

22	Gazete_Yenicag	Center	MHP	MHP	MHP	MHP	MHP	MHP
23	yenisafak	Right	AKP	AKP	AKP	AKP	AKP	AKP
24	yurtgazetesi	Left	Left-1	CHP	CHP/HDP	CHP/HDP	CHP	CHP
25	2023Gazete	Center	MHP	MHP	MHP	MHP	MHP	MHP
26	abcgazete	Left	Left-2	Left	CHP/HDP	CHP/HDP	CHP	CHP
27	artigercek	Left	Left-2	HDP	CHP/HDP	CHP/HDP	HDP	HDP
28	BeyazGazete	Right	AKP	AKP	AKP	AKP	AKP	AKP
29	bianet_org	Left	Left-1	HDP	CHP/HDP	CHP/HDP	HDP	HDP
30	DikenComTr	Left	Left-1	HDP	CHP/HDP	CHP/HDP	HDP	HDP
31	dokuz8haber	Left	Left-2	HDP	CHP/HDP	CHP/HDP	HDP	HDP
32	ensonhaber	Right	AKP	AKP	AKP	AKP	AKP	AKP
33	EtikHaber	Center	MHP	MHP	MHP	MHP	MHP	MHP
34	gazetebirlik	Right	AKP Leaning	AKP Leaning	Undefined	Undefined	AKP-Leaning	AKP-Leaning
35	GazetecilerCom	Center	Center-2	Center	CHP/HDP	Undefined	Undefined	Centrist
36	gazeteduvar	Left	Left-2	HDP	CHP/HDP	CHP/HDP	HDP	HDP
37	gazeteistiklal	Right	Center	Right-Leaning	AKP	Undefined	Right-Leaning	AKP-Leaning
38	Gazeteport_com	Left	Left-2	Left	CHP/HDP	CHP/HDP	CHP	CHP
39	gercekgundem	Left	Left-2	Left	CHP/HDP	CHP/HDP	CHP	CHP
40	GrihatHaber	Left	Left-2	Left	CHP/HDP	CHP/HDP	CHP	CHP
41	Haber7	Right	AKP	AKP	AKP	AKP	AKP	AKP
42	Haberler	Center	Center-2	Center	AKP	Undefined	Undefined	Centrist
43	habervaktim	Right	AKP	AKP	AKP	AKP	AKP	AKP
44	internethaber	Right	AKP	AKP	AKP	AKP	AKP	AKP

**Table 4 (Continued)**

45	medyafaresi	Center	Center-2	Center	CHP/HDP	Undefined	CHP	Centrist
46	medyaradar	Center	MHP	Center	AKP	Undefined	Undefined	Centrist
47	odatv	Left	Left-1	CHP	CHP/HDP	CHP/HDP	CHP	CHP
48	sivilmedyahaber	Right	Center	Right-Leaning	AKP	AKP	AKP	AKP
49	solhaberportali	Left	Left-1	CHP	CHP/HDP	CHP/HDP	CHP	CHP
50	t24comtr	Left	Left-1	HDP	CHP/HDP	CHP/HDP	HDP	HDP
51	turktimeCom	Left	Left-2	Left	Undefined	Undefined	Right-Leaning	Centrist
52	ulkucumedyacom	Center	MHP	MHP	MHP	MHP	MHP	MHP
53	YonHaber	Left	Left-2	Left	CHP/HDP	CHP/HDP	CHP	CHP

Table 4 illustrates two highly consistent media networks in which news outlets are clustered into different political or ideological positions. While  $r$  denotes resolution parameter, “NC” is the abbreviation for “number of clusters” in each network. For example, the third column in Table 4 shows the “selective exposure (S.E.) network” - *which is derived from news outlets’ overlap of co-subscribers*- with the resolution parameter of 1. In other words, when the resolution parameter is set to 1, Louvain clustering algorithm partitions this selective exposure network into 3 different clusters, which are manually identified as Right, Center and Left. While “right” and “left” points to pro-government and left-oriented oppositional outlets respectively, “center” points to outlets that are ideologically between them. Note that the outlets positioned in the center doesn’t necessarily mean they are neutral or moderate. Instead, their positions imply that they are not a core member of either first (Right) or the second (Left) cluster. Indeed, focusing on these outlets reveal that they might be a mixture of MHP-leaned (such as *ulkucumedy* and *Gazeteortadogu*) and moderate (such as *haberler.com* and *gazeteciler.com*) outlets.

Fourth and fifth columns in Table 4 partition the selective exposure network into more clusters with a higher resolution parameter ( $r=1.3$  and  $r=1.5$  respectively). Creating more clusters enable labeling them with party names, as most of the news outlets in clusters give important cues about their relationship with certain political parties. For example, in these columns, a cluster manually labelled as AKP consists of strongly pro-government newspapers such as *Aksam*, *Sabah*, *Star*; while CHP-labelled cluster consists of newspapers that are highly oppositional with a left slant, such as *Cumhuriyet* and *Sozcu*. On the other hand, MHP-labelled cluster includes outlets such as *ulkucumedy*, *gazeteortadogu* and *Yenicag*, which are publicly perceived as strongly pro-MHP.

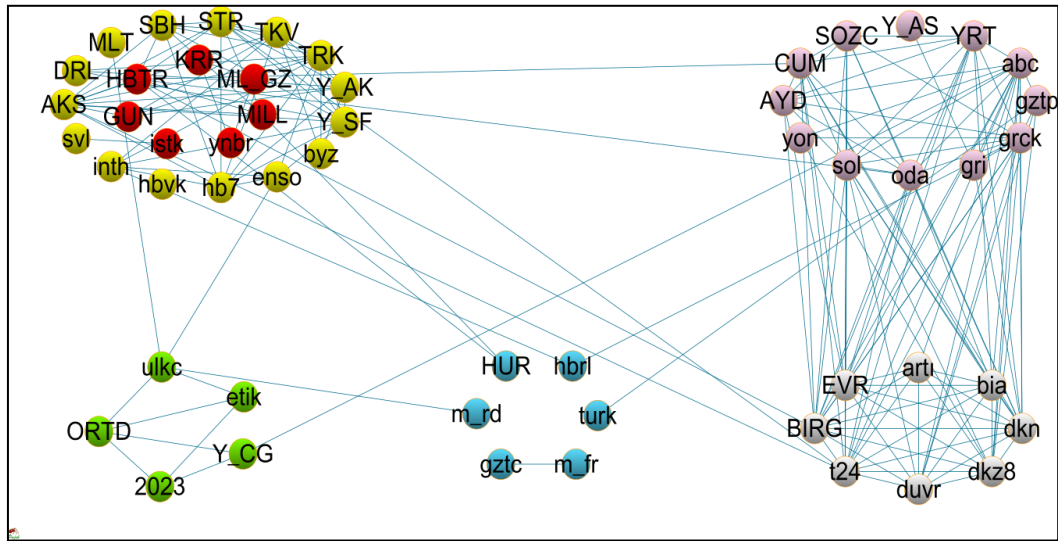
It can be seen from Table 4 that higher resolutions produced more clusters both in Selective Exposure (S.E.) and Partisan Selective Exposure (Partisan S.E.) networks. While standard resolution with parameter 1 gave core ideological groups of news outlets, higher resolutions partitioned those groups into smaller clusters with more specific political positions. Interestingly, both in S.E. and Partisan S.E. networks, CHP and HDP clusters were merged in  $r=1$  and  $r=1.3$ , and could be partitioned only in  $r=1.5$ , whereas core AKP cluster was fixed beginning from the standard parameter  $r=1$ . On the other hand, pro-AKP and pro-MHP clusters never merged at lower resolution parameters, indicating a strong association between pro-CHP and pro-HDP followers on Twitter, as well as a weaker association between pro-AKP and pro-MHP followers on Twitter. These results also imply an existence of ideological polarization between left-oriented (i.e., secular, Kemalist, pro-Kurdish) followers and conservative (i.e., Islamist, nationalist) followers, along with a political polarization between pro-government and oppositional groups.

Strikingly, outlets' cluster positions in S.E. network is very consistent with their corresponding cluster positions in Partisan S.E. network. In statistical terms, there is a strong relationship between outlets' clustering positions in selective exposure and partisan selective exposure network in resolution 1 ( $r_s = 0.92$ ,  $p < 0.01$ ), resolution 1.3 ( $r_s = 0.84$ ,  $p < 0.01$ ), and resolution 1.5 ( $r_s = 0.61$ ,  $p < 0.01$ ). For example, out of the 12 outlets which is clustered as pro-AKP in S.E. network, 11 outlets (92%) are labelled as pro-AKP, whereas the other one (Gunes newspaper) is labelled as right-leaning in the Partisan S.E. network. When looking at the other side, out of the 16 outlets which is clustered as pro-AKP in Partisan S.E. network, 11 (69%) are



clustered within pro-AKP media group, whereas the remaining 5 outlets are clustered as Right-leaning group in S.E. network. Therefore, although higher resolution parameters lead to more clusters with more political and ideological labels which in turn lower the level of statistical association between clustering positions of outlets in S.E. and Partisan S.E. networks, there is not a single outlet which is clustered in oppositional sides in these networks.

As a final step through outlets' party categorization, each outlet's cluster position in each network with different resolution parameters are compared. When there is a strong match in clusters between each network, the outlet is categorized into that party-associated cluster. For example, the 7<sup>th</sup> row in Table 4 illustrates the different cluster positions of Gunes Newspaper in each network. More specifically, that newspaper is clustered as Right -AKP - AKP - AKP - Undefined - Right Leaning - Center respectively. It can be seen that that newspaper has tight bonds with AKP, but not that enough to include it into the core pro-AKP media group. Therefore, as a final categorization, Gunes is clustered within AKP-Leaning media group. By investigating and comparing each newspaper's positions in networks, their political identification is manually determined and specified in 10<sup>th</sup> column in Table 4, which is labelled as "Partisan Clustering". See the illustration of Partisan Clustering network as a graph in Figure 3.



**Figure 3.** Partisan Clustering of News Outlets. Yellow, red, green, sky-blue, purple, and grey circles represent pro-AKP, AKP-leaning, pro-MHP, Centrist, pro-CHP and pro-HDP outlets respectively. Uppercase labels denote abbreviation of print newspapers, whereas lowercase labels denote abbreviation of digital-only newspapers. Links among outlets represent co-subscription relationship. For a better visualization, lines with Phi values lower than 0.2 are excluded from the network.

Figure 3 reveals a strong association between pro-CHP and pro-HDP media clusters based on the dense co-followership links between the outlets from each cluster. At the same time, it reveals almost no political association between pro-AKP and pro-MHP outlets as the outlets from each group of media cluster have almost no co-followership overlap. Moreover, this network demonstrates that people who mostly follow pro-MHP outlets on Twitter are ideologically isolating themselves from both pro-government and oppositional media clusters.

#### 4.1.3.2. Measuring Twitter Users' Partisan Leanings

It was explained that news outlets' political association with political parties was a precondition for identifying partisan selective exposure. As this precondition is met in the previous section, the second step for

measuring partisan selective exposure is to identify each Twitter user's political predisposition. Partisan selective exposure occurs among people whose political predispositions match with political predispositions of news outlets. Therefore, this step focuses on identifying each Twitter user's political proximity with a political party.

Previous studies on political Twitter networks note that Twitter users tend to follow accounts which have politically similar predispositions with them (Pablo Barberá & Gaurav Sood, 2016). Barberá (2015) notes that following decisions on Twitter is very hard to be ideologically challenging, as cross-ideological views increase cognitive dissonance and as it also creates opportunity costs by decreasing the likelihood of being exposed to like-minded information due to the limited time to be allocated on Twitter. The findings are consistent with Barberá's theoretical arguments. For example, Himelboim et al. (2013) found that being exposed to cross-ideological political information through the tweets of the users that are being followed is unlikely, as following-decisions occur among politically homogeneous Twitter users. Similarly, Boutyline and Willer (2017) investigated the followers of politicians and used this as a proxy for identifying political orientations of these followers. Halberstam and Knight (2016) estimated the ideology of a Twitter user based on the party affiliation of politicians that they mostly follow on Twitter. He coded a Twitter user as Democratic if she follows more Democratic politicians on Twitter than Republican politicians. Al Zamal, Liu and Ruths (2012) showed that, which political accounts a user follow on Twitter allows to infer her political predisposition even in the absence of any additional information about her. As a last example, Du and Gregory (2017) demonstrated that, in line with homophily principle, new following links are at least 3-4 times more likely to be created within politically homogeneous communities than between

mutually heterogeneous communities. They also found that Twitter users are more likely to cancel following accounts if they are members of the counter-ideological communities.

#### **4.1.3.2.1. Operationalization (Political Predispositions of Twitter Users)**

Building on these insights, -and as Twitter data lacks the information to directly measure the political predispositions of Twitter users-, this thesis uses following links to political entities, *defined here as political party and party deputy accounts*, to infer each Twitter user's political predispositions as well as their strength of partisanship. As following a political party and its deputies on Twitter is a significant indicator of favorability toward that party and its ideology (e.g., Al Zamal, F, Liu, W., & Ruths, D., 2012; Boutyline & Willer, 2017; Halberstam & Knight, 2016), more deputies of a party followed by a twitter user implies a greater favorability toward that party. Accordingly, for operationalization of party identification, each Twitter user's (n=2790339) followees including political party official accounts and deputy accounts are counted.

It should be noted that each party has disproportionate number of deputy accounts on Twitter (AKP = 285, CHP = 126, HDP =49, MHP =33). Thus, this disproportionality would create a difference for each party in terms of average and maximum number of deputies that is followed by Twitter users. To give an example, a Twitter user who follows 33 deputies of MHP would have a full score in terms of favorability toward MHP, as she follows all the deputies from that party. However, it would be unreasonable from a pro-AKP Twitter user to follow all 285 AKP deputies who have a Twitter account. To get a standardized measure of party identification ranging from 0 (no identification) to 1 (full identification), a

few preliminary steps are followed. First, each political party's deputy numbers lying within the 1.96 standard deviation of the mean is calculated.

To exclude extreme Twitter users who deviate from the 95% of the Twitter sample in terms of following excessive number of deputies, 1.96 standard deviations from the mean is calculated for each party. Deputy numbers that are being followed by Twitter users falling outside the z-score range of 0 – 1.96 are regarded as outlier. Accordingly, Twitter users who follows more deputies than the upper limit of the standard deviation is assumed to follow maximum number of deputies that fall within 1.96 standard deviation. Table 5 shows the distribution of party deputy numbers based on their followers on Twitter.

**Table 5**

*Z-Score distribution of party deputies based on their followers on Twitter*

Party	Mean	Z-score	Twitter Followers	Min.	Max.	%
AKP	5,7	0-1.96	1829702	1	43	65
		1.96-2.58	38290	44	79	1
MHP	1,05	0-1.96	1518032	1	7	54
		1.96-2.58	17984	8	11	0,6
CHP	3,9	0-1.96	2289359	1	17	82
		1.96-2.58	57160	18	27	2
HDP	1,4	0-1.96	914667	1	22	32
		1.96-2.58	20265	23	37	0,7

Table 5 shows that, of the whole Twittter sample data that comprises 2.790.339 Twitter users, 1.867.992 (1829702 + 38290) users follow at least one AKP deputy. For those users, 95% of the area under a normal curve, *which corresponds to a number of AKP deputies ranging from 1 to 43*, lies within roughly 1.96 standard deviations of the mean ( $\bar{x} = 5,7$ ), whereas 99% of the area under a normal curve, *which corresponds to a number of AKP deputies ranging from 44 to 79*, lies within roughly 2.58 standard deviations of the

mean ( $\bar{x} = 5,7$ ). Therefore, although AKP has 285 deputies that have an account on Twitter, users who follow more than 79 deputies are regarded as outlier and no matter what the number of deputies that they follow from AKP, they are given a score of 79, which is the maximum number falling within 2.58 standard deviations of the mean for AKP deputies. As can be seen from Table 5, numbers higher from 79, 11, 27, and 37 are regarded as extreme and outlier for AKP, MHP, CHP and HDP deputies respectively.

It might be put forward that following only one AKP deputy would not be considered to imply same strength of identification toward AKP compared to following 79 deputies. Therefore, these numbers represent each Twitter user's strength of identification toward a specific political party. For example, while following 79 AKP deputies point to maximum favorability toward AKP, following 27 CHP deputies imply maximum favorability toward CHP.

As a second step, the number of deputies that are followed by each Twitter user is investigated for measuring the strength of party identification. The operationalization of this measurement is as follows: the deputies of a party that is followed on Twitter divided by the total number of deputies from that party gives a score of party identification strength ranging from 0 to 1. However, as the distribution of deputy numbers that are followed are positively skewed and not normally distributed, direct division gives erroneous scores especially for comparing these scores across other parties. Consider a Twitter user who follows 44 AKP deputies. By simply dividing 44 by 79, we have a 0.55 favorability score toward AKP, which refers to the strength of pro-AKP identification. However, we already know from Table 5 that 68% of Twitter audience ( $z=1$ ) follow pro-AKP deputies ranging from 1 to 43. Therefore, it would be expected to have

higher than 0.68 favorability score toward AKP with 44 pro-AKP accounts being followed. Therefore, instead of dividing 44 by 79, a base-10 logarithmic transformation is conducted and  $\log(44)$  is divided by  $\log(79)$ , which gives a more appropriate score; namely 0.86. In brief, strength of party identification can be formulized as follows;

$$\text{Favorability}_{(Party1)} = \frac{\log(\# \text{ deputies of Party1 being followed})}{\log(\# \text{ all deputies of Party1})}$$

Where “# deputies of Party-1 being followed” refers to the number of political party deputies (including the official account of that party) followed from Party-1, and where “#all deputies of Party-1” refers to the highest deputy number from Party-1 that falls within the 1.96 standard deviations from the sample mean (see Table 5).

In sum, this logarithmic division gave a party-favorability score ranging from 0 to 1 for each user, which refers to strength of party identification. To classify each Twitter user as pro-AKP, pro-CHP, pro-HDP, pro-MHP or Mixed based on their party affiliation of politicians that they follow, several steps are followed.

(1) For Twitter users who follow more than 3 deputies, they were identified with a political party if their favorability score toward that party is higher than all other party favorability scores. (2) For Twitter users who follow exactly 3 deputies from a specific party, they were identified as “leaned toward that party” if they followed at most 1 deputy from other parties. (3) Twitter users who have the same highest favorability score for more than one party are coded as Mixed. (4) Twitter users who follow less than 2 deputies are also coded as Mixed. Table 6 show the party identifications of Twitter users as well as their party identification strength.

**Table 6***Strength of Party Identifications Illustrated as Three-Quartiles*

	Leaned	%	Weak (0 - 0.25)	%	Moderate (0.26-0.75)	%	Strong (0.76 - 1)	%	Sum
AKP	60.327	8	173.689	23	319.831	43	196.136	26	749.983
CHP	150.826	19	166.589	21	252.366	31	238.453	30	808.234
HDP	27.302	12	52.887	23	97.195	43	50.905	22	228.289
MHP	12.121	15	19.597	25	25.269	32	22.609	28	79.596
Mixed	-		-		-		-		924.237

As seen from Table 6, strength of party identification is categorized into 4 classifications. In addition, Twitter users who have either followed less than 3 deputies or have equal values of party identification strengths are labelled as “mixed” users. These followers mostly represent politically less interested and non-partisan audience.

The first classification (“Leaned”) represents party-leaned twitter users who follow exactly 3 party deputies of a specific party (including party official account) and who follow less than 2 deputies from any other party. Weak party identification refers the number of Twitter users who fall within first quartile (25%) of pro-party audience based on their party-favorability score. Moderate and Strong party identification refers the number of Twitter users who fall within 25%-75% and last quartile (76%-100%) of pro-party audience respectively, based on their party-favorability score. Therefore, Twitter users who are within highest 25% quartile in terms of following higher numbers of deputies of a specific party is regarded as having a strong party identification, whereas Twitter users who are within lowest 25% quartile in terms of following lower numbers of deputies of a specific party are regarded as having a weak party identification. The party supporters falling between the first and third quartiles are regarded as



having a moderate party identification toward that party. It should be noted that these quartiles are identified based on each twitter user's party identification strength (favorability scores.) Table 7 illustrates these values for each party and for each quartile.

**Table 7**

*Party Identification Strength Illustrated as Quartiles for each Political Party Supporters*

	1st Quartile (25%)	2nd Quartile (75%)	3rd Quartile (100%)
AKP	0.40	0.55	0.70
CHP	0.48	0.58	0.74
MHP	0.65	0.84	1,00
HDP	0.44	0.60	0.74

Table 7 shows that, all political party followers except from MHP have similar party strength values. For example, the first 25% of pro-AKP Twitter followers who follow least number of AKP deputies compared to other higher quartiles, have a maximum party identification strength of 0.40, which is very similar for CHP (0.48) and HDP (0.44) followers. Similarly, party supporters within the highest quartile have also similar party identification strengths (AKP=0.70, CHP=0.74, and HDP=0.74). However, for each quartile, Twitter followers who are identified as pro-MHP have higher party strength values. This is mostly due to the fact that while media clusters categorized as pro-AKP, pro-CHP and pro-HDP have higher numbers of news outlets within them (15, 12, and 8 respectively), media cluster associated with MHP has only 5 news outlets within it. Therefore, unlike other Twitter followers who have higher options to select among like-minded outlets, pro-MHP followers have fewer options, at most 5 outlets to follow, which increases their likelihood to follow more outlets compared to other partisans. Accordingly, following more outlets from a

partisan media cluster increases the strength of identification toward that political party.

#### **4.1.3.3. Measuring Partisan Selective Exposure on Twitter**

Now that both party-based classifications of news outlets and Twitter users are completed, the last stage of the method stands for matching these classifications and measuring the extent of match. In brief, partisan selective exposure means consuming news outlets whose political slant matches with that of the audience (Gentzkow & Shapiro, 2011; Gvirsman, 2014; Johnson et al., 2009; Stroud, 2010; Yonghwan Kim, 2015). This thesis builds upon this notion by suggesting that (1) following politically like-minded news outlets on Twitter refers to partisan selective exposure, and (2) following a politically dissonant news outlet refers to counter-party and thus cross-cutting exposure. Accordingly, it hypothesizes that Turkish Twitter users who are interested in politics are more likely to follow news outlets that share their political predispositions, and less likely to follow cross-cutting outlets that are slanted away from their political views.

##### **4.1.3.3.1. Operationalization (Partisan Selective Exposure)**

As selective exposure includes not only consuming like-minded political information but also avoiding cross-cutting political views, the measurement is designed to capture both exposure and avoidance. Accordingly, selective exposure to party-associated news outlets are operationalized as follows:

$$100 \times \frac{Selectivity_{(cluster1)}}{(Selectivity_{(cluster1)} + Selectivity_{(cluster2)} + Selectivity_{(cluster3)} + Selectivity_{(cluster4)})}$$

Where selectivity toward a party-associated media cluster simply represents the number of outlets followed by a Twitter user that are clustered within that media group.

However, as the number of newspapers in each party-associated media cluster (AKP: 15 outlets, CHP:12 outlets, HDP: 8 outlets, and MHP: 5 outlets) differs, an adjusted and standardized selective exposure index is required which would enable to compare these indices across different media clusters. For example, for a pro-MHP Twitter user who follows 5 out of 5 (100%) news outlets that is clustered within pro-MHP media cluster and 5 out of 12 (40%) news outlets within pro-CHP media cluster, her pro-MHP selective exposure index would be  $100 * (5/(5+4+0+0))$ , which corresponds to only 55. However, her selective exposure score would be expected to be higher considering her full selectivity toward her like-minded media cluster.

Therefore, this selective exposure measure is adjusted by first finding the least common multiple (lcm) of maximum newspaper numbers within each media cluster (15, 12, 8, and 5), which corresponds to 120. Second, these party-associated newspaper numbers are divided by 120 to get a standardized coefficient for a selectivity measure, which is 8 for pro-AKP, 10 for pro-CHP, 15 for pro-HDP and 24 for pro-MHP media clusters. Last, the number of outlets followed within pro-AKP, pro-CHP, pro-HDP and pro-MHP media clusters are multiplied by 8, 10, 15, and 24 respectively to get an adjusted selective exposure index. The final formula for measuring (say pro-AKP) partisan selective exposure is:

$$100 \times \frac{8 \times \text{Selectivity}_{(\text{Pro-AKP Media Cluster})}}{(8 \times \text{Selectivity}_{(\text{pro-AKP})} + 10 \times \text{Selectivity}_{(\text{pro-CHP})} + 15 \times \text{Selectivity}_{(\text{pro-HDP})} + 24 \times \text{Selectivity}_{(\text{pro-MHP})})}$$

In this revised measure, a pro-MHP Twitter user who follows 5 outlets from pro-MHP and 5 outlets from pro-CHP media cluster will have, a partisan selective exposure index of 70<sup>5</sup>, which seems to be very reasonable.

As such, operationalized as a score ranging from 0 (no partisan exposure) to 100 (maximum partisan selective exposure), partisan selective exposure increases when being exposed to more like-minded outlets and when being exposed to less politically dissonant outlets.

Note that, consistent with the theoretical framework of partisan selective exposure, this measurement strategy reduces the like-minded news exposure value of a partisan if she is exposed to cross-ideological outlets that are clustered within other party-associated media clusters. Otherwise, it would be misleading to give a full partisan selective exposure score to a pro-party user if she would follow maximum numbers of outlets both from in-party and out-party media clusters. In the previous example, assume that the pro-MHP Twitter user followed 5 outlets within pro-MHP and 12 outlets within pro-CHP media clusters. Not taking into consideration out-party outlets followed on twitter would give that user a partisan selective exposure score of 100. However, the formula used in this measurement will give that pro-MHP user a selectivity score of 50<sup>6</sup>, which is highly consistent with the definition of partisan and cross-cutting selective exposure in the literature. In sum, for a maximum partisan selective exposure with a value of 100, not only selective exposure to like-minded pro-party outlets in a media cluster but also selective avoidance to

---

<sup>5</sup>  $(100 * ((24 * 5) / ((24 * 5) + (10 * 5) + 0 + 0)))$

<sup>6</sup>  $(100 * (120 + 120 + 0 + 0))$

all pro-party outlets from other politically-discrepant media clusters are required.

#### 4.2. Measuring Partisan Polarization on Twitter

Partisan polarization is defined as the absolute value of the difference between favorability scores of competing parties or their candidates (e.g., Stroud, 2008, 2010; Gvirsman, 2014). This thesis expands on this notion and uses the absolute value of the difference between favorability score toward most favored party and toward other parties as an indicator of partisan polarization on Twitter. More clearly, partisan polarization is defined as;

$$Polarization_{(party-1)} = |Fav_{(party-1)} - \frac{Fav_{(party-2)} + Fav_{(party-3)} + Fav_{(party-4)}}{3}|$$

where  $Fav_{(party-1)}$  denotes the favorability score (*the indicator for strength of party identification*) of a Twitter user toward the most favored party, which ranges from 0 (no party identification) to 1 (strongest party identification). Note that these favorability scores are calculated based on the extent of standardized number of deputies followed from each political party (see chapter 4.1.5 for the formulation). As party identification strengths are illustrated with a range from 0 to 1, the corresponding polarization scores also range from 0 (no polarization) to 1 (maximum polarization) for each party.

As such, maximum polarization refers to a situation where a user follows maximum number of deputies from a political party without following any deputy or party account from any other political parties. On the other hand, minimum polarization refers to a situation where a user follows the deputies of all four parties proportionately. Garimella and Weber (2017) uses a similar measure for political polarization on Twitter.

They define polarization for a Twitter user as obtaining (following on Twitter) or engaging in (retweeting/hashtagging on Twitter) political information that is restricted only with one side of the political spectrum. Similarly, they note that following political accounts from both sides of the political spectrum signs for a non-polarization.

It might be argued that implications of party identification strength and political polarization are very similar. Indeed, in most studies, the basic difference between them is that while party identification strength is measured by asking respondents to define themselves as moderate, weak or strong partisan, polarization is measured by asking them to define their attitudes both for their own party and for oppositional party (e.g., Stroud, 2010). Accordingly, the main difference between them is that the former refers to the strength of attitudes for the supported party, and the latter refers to the absolute difference between the attitude strengths of supported and oppositional party. Therefore, assuming that following a party/deputy account indicates strength of political proximity toward a party, and not following a party/deputy account indicates political distance, subtracting the average of favorability scores toward oppositional parties from the favorability score toward the supported party gives a reasonable polarization index. Furthermore, this polarization index is a standardized measure which can be compared across all users.

#### **4.3. The Association Between Partisan Selective Exposure and Polarization**

Past studies reveal that politically consistent news exposure reinforces political attitudes and polarization toward political parties, whereas cross-ideological news exposure weakens these polarized attitudes (e.g., Arceneaux et al., 2012; Garrett et al., 2014; Knobloch-Westerwick, 2012;

Levendusky, 2013). This thesis aims to investigate the relationship between the amount of partisan media consumption and the level of polarization on Twitter, with a Turkish Twitter community context. Accordingly, it hypothesizes that there is a positively strong association between the level of partisan selective exposure and polarization for politically interested Turkish Twitter users.

#### **4.3.1. Variables**

Following recent researches demonstrating that partisan selective exposure leads to political polarization rather than vice versa (M. S. Levendusky, 2013; Stroud, 2010; Tsfati & Chotiner, 2016), partisan selective exposure is defined as the independent variable and polarization is defined as the dependent variable.

To investigate the relationship between partisan selective exposure and polarization, a simple correlation between the indices of partisan selective exposure and political polarization would not be efficacious as this association might be the result of some other variables which would have an effect on both partisan selective exposure and political polarization. In other words, to rule out the possibility of misleading and erroneous results, the analysis of their association must account for some political variables (which are called control variables). For example, as some researchers note (see e.g., Iyengar & Hahn, 2009; Lelkes et al., 2017), politically interested online users might be exposed to more partisan news content compared to people with less political interest, which in turn leads to more political polarization. In such a circumstance, it would be political interest rather than partisan selective exposure, which leads to political polarization. Similarly, past studies reveal that except from political interest, political discussion, partisan strength and media use frequency are also significant

variables that might influence the relationship between partisan selective exposure and polarization (Stroud, 2010). Therefore, to see the pure impact of partisan selective exposure on polarization, control variables are also included into the analysis.

To create control variables, a random sample of 45.880 twitter users out of 2.790.339 are selected. Followingly, Twitter's REST API is used to collect the recent tweets of those 45.880 users. As Twitter restricts to collect up to 3.200 tweets per user in reverse chronological order, the last 3.200 tweets for each user (where available) are collected in February 2018. To exclude fake accounts (spam bots), passive users, and very popular accounts (political organizations, journalists, political elites etc.) that are not representative of an ordinary user, a) users who have not posted at least a tweet in the past one month, b) users who have less than 50 tweets in total, and c) users who have more than 10.000 followers are discarded. This gave a final sample size of around 5 million tweets, which belong to 35.766 unique Twitter users. Note that these users follow at least two political news outlets and two political party or deputy accounts. The subsequent regression analyses for independent variable (partisan selective exposure), dependent variable (polarization), and control variables are performed based on this data. The control variables derived from this data are as explained below:

**Political interest** variable is measured for each Twitter user as the proportion of political tweets to the total tweets. Political tweets are identified by using text mining method. More specifically, each tweet is categorized as political if it included one of the 335 keywords that are indicators of politics. Otherwise, they are regarded as non-political tweets. These words are identified manually by investigating most frequently used



political keywords in the Tweet dataset corpus. See Appendix B for the political keywords.

**Political Discussion** variable is created based on hashtags. A Twitter hashtag is a keyword or topic preceded by the # character (e.g., #akpartigeliyor, #akpİstifa), which is entered into the tweet along with the message content. Past studies on Twitter demonstrate that hashtags consisting of controversial political topics are strong indicators of political discussion among ideologically oppositional groups (e.g., Devin Gaffney, 2010; Hemphill, Culotta, & Heston, 2016; Romero, Galuba, Asur, & Huberman, 2011; Small, 2011). Based on these insights, to measure political discussion, firstly, hashtags with politically controversial topics are identified. To minimize noise due to low volumes, most frequent hashtags that are used by at least 1500 distinct Twitter users and that appeared in at least 1000 different tweets are selected for the analysis. Secondly, among these hashtags, the political controversial topics are manually determined, which gave a total of 577 hashtags. Finally, political discussion variable is measured for each user as the proportion of tweets including politically controversial hashtags to her total tweets. See Appendix C for the politically controversial hashtags.

**Media Use Frequency** variable, which shows how active a user in terms of using Twitter platform as a media source, is measured as the average number of tweets sent on a day. For example, a twitter user, who has sent a total of 1000 tweets (including retweets) within a range of 100 days has a score of 10, which shows the proportion of total tweets sent to the range of days which are between the date of the first tweet and the date of the last tweet.

### **4.3.2. Measurement of the Variables**

To see the association between partisan selective exposure and political polarization, a multiple regression analysis with interaction terms is conducted. Multiple regression allows to investigate the impact strength of predictor/independent variable(s) on the outcome/dependent variable while controlling for the effects of other external/control variables. As such, it also allows to determine the relative contribution of each predictor and control variable to the total variation in polarization. When all other control variables along with the partisan selective exposure are included into the regression model, if a great amount of variance in political polarization is explained by partisan selective exposure, then it can be concluded that partisan selective exposure indeed predicts and leads to polarization. Otherwise, it should be concluded that other control variables have higher impact on both selectivity and polarization.

As partisan selective exposure includes both partisanship and like-minded media exposure, interaction terms between party identification and selective media exposure are used to investigate their combined impact on polarization. For example, to model pro-AKP users' (partisanship) pro-AKP media exposure (selective exposure) on polarization, pro-AKP partisanship and pro-AKP media exposure on Twitter are included into the regression analysis as an interaction term. The presence of a significant interaction between these two predictor variables would indicate that pro-AKP partisanship and pro-AKP media exposure interact together in their effects on the outcome variable, political polarization. Therefore, their interaction would imply that the effect of pro-AKP media exposure on polarization differs at different levels of pro-AKP partisanship. Likewise, the effect of

pro-AKP partisanship on polarization would be different at different values of pro-AKP media exposure<sup>7</sup>. As Stroud (2010) notes, including an interaction term between partisanship and like-minded media exposure enables to make inference about (a) the impact of consuming pro-party news outlets and (b) whether this impact is reinforced when the audiences' political party affiliations correspond with that of news outlets, as would be expected by the theoretical concept of partisan selective exposure. Therefore, a statistically significant interaction term means that selective exposure to pro-party news outlets on Twitter reinforces polarization among partisans who are affiliated with the same party.

#### **4.4. Validation of the Polarization and Partisanship Measures**

##### **4.4.1. Alternative Measurement of Polarization**

To strengthen and validate measurement of partisan polarization, another polarization index is created from the Twitter database. Past studies show that Twitter users retweet other users with whom they share the same political views. Moreover, retweets consisting political content occur among highly partisan Twitter users that are segregated into ideologically homogeneous political networks. The connectivity between politically-opponent users is very limited based on retweets, so they are strong indicators of support for attitude-consistent information (Conover et al., 2011).

Therefore, most studies focusing on ideological polarization on Twitter measures it by analyzing users' retweets of tweets which belong to attitude consistent and attitude discrepant accounts. Conover et al. (2011)

---

<sup>7</sup> In SPSS, polarization is tested by adding an interaction term in which variables of the main effects (partisanship and pro-party media exposure) are first mean-centered and then multiplied. Following the same example; Political polarization = pro-AKP partisanship + pro-AKP media exposure + (pro-AKP partisanship X pro-AKP media exposure) + Control Variables

analyze 250.000 political tweets in an election period and find that there is an extreme polarization on Twitter audience based on disproportionately retweeting ideologically like-minded accounts. Similarly, Halberstam and Knight (2016) demonstrate a very high polarization on Twitter such that 91% of tweets which belong to Democratic candidate accounts are retweeted by liberal audience on Twitter, whereas 99% of tweets which belongs to Republican candidate accounts are retweeted by conservative audience on Twitter. Likewise, studies reveal that partisans chose to retweet a political tweet if its author shares the same political views with them (Yardi & Boyd, 2010). However, they don't choose to retweet a political tweet if its author belongs to the community from the other side of the political spectrum (Borondo, Morales, Benito, & Losada, 11). As a last example, a study in Spain investigated the structure of a network which is created based on retweeting politically center-right El-Mundo newspaper and center-left El-Pais newspaper. The analysis revealed that audiences on Twitter are extremely polarized such that users who retweet one newspaper almost never retweets the other newspaper which has politically discrepant slant compared with the former (Borondo et al., 11).

Expanding on the notion of these studies, a polarization index is created by investigating political retweet patterns of a sample Twitter audience. First, a random sample of 35.766 users from the Twitter population (n=2.790.339) in the database is selected<sup>8</sup>. Second, political accounts that are retweeted by at least 1.000 different users are manually categorized as either pro-government or oppositional, which gave a total of 523 accounts. These accounts include politicians, newspapers, journalists, lawyers, Twitter phenomenons, non-governmental organization leaders,

---

<sup>8</sup> For a more detailed explanation about selection criteria, see Chapter 4.3.1.

parody accounts and artists as well (See Appendix A for the whole list). Third, each user is given a score showing that, of all the retweets, what percentage belongs to pro-government and what percentage belongs to oppositional accounts. Last, the retweet polarization index, ranging from 0 (no polarization) to 100 (complete polarization) is calculated by finding absolute difference between these scores. For example, a twitter user whose pro-government retweets constitute 70% of her all retweets, and whose oppositional retweets constitute 10% of her tweets will have a polarization index of 60 ( $|70 - 10|$ ). Based on this measurement strategy, all sample users' retweet polarization indices are calculated. Considering that the Twitter accounts that are retweeted by the sample users are categorized as either pro-government or oppositional, this index can be regarded as an indicator of ideological polarization rather than partisan polarization.

#### **4.4.2. Alternative Measurement of Partisanship**

Although there are many academic studies noting that following a political account on Twitter is a significant indicator for partisanship and its strength (see references in chapter 4.1.5), it might still be argued that the partisanship measurement used in this thesis might be misleading for identifying political predispositions as following on Twitter might not always mean political endorsement. To clarify this important suspicion, a validation of the partisanship measure is performed. Expanding on the notion that different political parties create and use different frames about political issues, concepts and terms which influence their supporters' behaviors and choices (Monroe, Colaresi, & Quinn, y.y.; Scheufele & Tewksbury, 2007), it is expected that pro-government Twitter users chose "ak parti" or "akparti", whereas oppositional accounts chose "AKP" when framing that political party.

Accordingly, each Twitter user's tweets that was collected for regression analyses are text-mined. Three variables are created, which shows a) how many "ak parti" or "akparti" words take place in the tweets, b) how many "akp" words take place in the tweets, c) whether Twitter users are either "pro-AKP" or "oppositional" in terms of using more "akparti/ak parti" words or more "akp" words respectively in their tweets.

The categorical variable ("pro-AKP" and "oppositional") is used to investigate whether measurement of pro-AKP partisanship based on users' dominant following ties to AKP deputies and to AKP official party account is consistent with pro-AKP partisanship measured based on their framing the ruling party as "akparti" or "ak parti" in their tweets.

## CHAPTER 6

### ANALYSES AND RESULTS

#### 5.1. Partisanship and Selective Exposure

The first research question of this study aims to discover whether and to what extent Turkish Twitter users practice partisan selective exposure to politically like-minded news outlets. Therefore, partisan and cross-cutting selective exposure values of Twitter users that are identified with a political party are illustrated in Table 8.

When looking at the values in Table 8, it is clear that Twitter audiences engage in partisan selective exposure by following political news outlets that support their political views much more than ones that oppose their political views. The segregation in terms of partisan and cross-cutting selective exposure is obvious. Moreover, this partisan selective exposure phenomenon is true for all four political party supporters on Twitter. Consistent with the literature (Stroud, 2008) higher selective exposure indices for strong partisans compared to Twitter users with lower party identification strength demonstrate that strength of political identification is a significant predictor of partisan selective exposure. In other words, as party identification strength increases, so does the index of partisan selective exposure. For example, while Twitter users who are strongly in favor of AKP have a partisan (pro-AKP) selective media exposure index of 72,5, this index is 50 for pro-AKP users having a weak party identification. Likewise, strong and weak pro-CHP audience have selective news outlet exposure value of 43,7 and 40,5 respectively.

**Table 8***(Partisan) Selective News Exposure to Pro-party News Outlets*

Twitter Users	Strength of Partisanship	Conservative Outlets			Left-Leaning Outlets		
		Pro-AKP	Pro-MHP	Cons.	Pro-CHP	Pro-HDP	Left
		S.E.	S.E.	S.E.	S.E.	S.E.	S.E.
Pro-AKP	Strong	<b>72,5</b>	3,7	76,3	9,5	9	19,6
	Moderate	<b>61,2</b>	2,9	64,6	12	11,2	25,8
	Weak	<b>50</b>	1,9	52,2	12,7	12,4	29,2
	Leaning	<b>48</b>	1,3	49,6	8,5	9,3	21,6
Pro-MHP	Strong	15,7	<b>58,5</b>	74,7	13	8,5	22,7
	Moderate	19,6	<b>45,2</b>	65,8	15,8	9,7	28,8
	Weak	23,6	<b>31,2</b>	55,7	17,3	10,2	33,4
	Leaning	26,3	<b>26,7</b>	53,6	11	5,7	22,2
Pro-CHP	Strong	8,1	2,9	11,6	<b>43,7</b>	35	86,5
	Moderate	7	1,8	9,5	<b>43,5</b>	29,7	87,5
	Weak	9,6	1,3	11,7	<b>40,5</b>	24	82,4
	Leaning	7,5	0,9	8,9	<b>38</b>	18,4	77,2
Pro-HDP	Strong	6,6	0,4	6,8	36,2	<b>68</b>	90,7
	Moderate	10,8	0,3	11,1	28,2	<b>60,7</b>	81,2
	Weak	15,8	0,3	16,3	24,5	<b>50,6</b>	71,0
	Leaning	18,4	0,2	18,7	20,7	<b>44,5</b>	62,4
Mixed		24,4	2	26,9	23	18	51,3

**Note.** The abbreviation “S.E.” denotes for selective exposure values, ranging from 0 (no exposure) to 100 (maximum exposure), for each political party as well as for each ideological position (conservative and left-wing). Ideologically conservative outlets represent the combination of pro-AKP and pro-MHP outlets, whereas ideologically left-wing outlets represent the combination of pro-CHP and pro-HDP outlets. Bold values in cells represent partisan selective exposure values.

On the other hand, in general, strength of party identification is negatively related with cross-cutting news exposure. Uncongenial and cross-cutting news exposure indices of AKP, CHP, HDP and MHP audience are all below 20 especially if the media cluster is from the other side of the ideological spectrum. Furthermore, while indices of cross-cutting selective exposure are very low, these values are generally higher for partisans that have a weaker party identification strength, showing that weak political



predispositions contribute more to cross-cutting news exposure compared to strong political predispositions. For example, like-minded news exposure is lower (50 vs. 72,5) and cross-cutting (pro-CHP) news exposure is higher (12,7 vs. 9.5) for users who have weak party identification compared to strong party identification for AKP. These proportions are similar and consistent across all political parties, suggesting that strength of political identification is positively related with partisan selective exposure and negatively related with cross-cutting news exposure.

Table 8 shows that users identified as pro-CHP and pro-HDP have mutually very high selective exposure values toward left-leaning media clusters. However, users identified as pro-AKP and pro-MHP doesn't have such high values toward conservative media outlets. For example, the selective exposure index for an average strongly pro-MHP audience toward pro-AKP media cluster is 15,3, whereas this index is more than twice as much (36,2) for an average pro-HDP audience with a strong party identification toward pro-CHP media cluster. Moreover, for CHP and MHP supporters, as party identification strength increases, the selective exposure index for other ideologically like-minded media cluster also increases. In particular, Twitter users who are politically in favor of CHP and HDP are ideologically far closer to each other compared to pro-AKP and pro-MHP Twitter users who are ideologically right-leaning.

When it comes to ideological rather than political alignment with media clusters (i.e. conservative and left-leaning outlets), the segregation becomes deeper. Exposure to conservative news outlets by strongly pro-AKP and pro-MHP users are 76,3 and 74,7 respectively. Similarly, exposure to ideologically left-leaning news outlets by strongly pro-CHP and pro-HDP users are 86,5 and 90,7 respectively. In sum, average conservative's

conservative media exposure is 64, whereas average oppositional audience's left-leaning media exposure is 84,4. These results indicate that left-leaning ideology (i.e., Kemalism, Secularism, socialism, pro-Kurdism) harbors a more ideologically homogeneous Twitter audience than right-leaning (ie., conservatism, political Islamism) ideology in terms of consuming ideologically like-minded political news outlets.

A part of the research question mentioned above investigates whether political parties (AKP, CHP, HDP and MHP) differ in terms of their grassroots' partisan or cross-cutting selective exposure level. Using a large sample data from Turkish Twitter users, results in Table 8 give enough evidence to suggest these politically diverse grassroots have almost equal levels of partisan selective exposure to like-minded news outlets. In addition, the results also give enough evidence that strength of political identification largely contributes to political news consumption preferences. In sum, Turkish Twitter users' political party association affect their political news diets on Twitter, no matter which political party they are in favor of.

While showing a clear evidence on partisan selective news exposure, whether and to what extent news outlets attract politically interested partisans is yet not apparent. Although Table 8 clearly shows that there is a strong tendency for pro-party Twitter users to follow news outlets that correspond with their political view, it doesn't give insights about how partisan/biased Turkish news outlets are in terms of attracting politically homogeneous or heterogeneous Twitter audience. To uncover this research question, each newspaper that is clustered within a political party are investigated in terms of its proportion of followers from four political parties as well as from the politically mixed users (See Table 9).

**Table 9***Partisan Selective Exposure and Odds Ratios of Pro-party Twitter Users*

News Outlets	Party-Cluster	Party Identification					Share	Odds Ratio
		AKP	CHP	HDP	MHP	Mixed		
Akşam	AKP	.50	.14	.05	.03	.28	.15	4,3 (AKP/o.)
Beyaz Gazete	AKP	.75	.12	.02	.04	.08	.01	6,8 (AKP/o.)
Diriliş Postası	AKP	.83	.07	.02	.02	.06	.01	11,8 (AKP/o.)
Ensonhaber	AKP	.57	.19	.04	.05	.15	.07	3,4 (AKP/o.)
Haber7	AKP	.67	.13	.04	.04	.13	.15	7,6 (AKP/o.)
Haber-vaktim	AKP	.75	.11	.02	.04	.08	.01	6,7 (AKP/o.)
İnternet-haber	AKP	.46	.28	.06	.06	.15	.04	1,8 (AKP/o.)
Milat	AKP	.63	.15	.03	.05	.14	.01	4,3 (AKP/o.)
Sabah	AKP	.48	.15	.05	.03	.30	.28	5,4 (AKP/o.)
Sivil Medya	AKP	.43	.22	.07	.06	.23	.01	1,8 (AKP/o.)
Star	AKP	.51	.14	.05	.03	.28	.19	5 (AKP/o.)
Takvim	AKP	.66	.16	.03	.04	.11	.03	4,7 (AKP/o.)
Türkiye	AKP	.71	.13	.02	.04	.09	.03	5,8 (AKP/o.)
Yeni Akit	AKP	.68	.16	.03	.03	.09	.04	4,9 (AKP/o.)
Yeni Şafak	AKP	.65	.15	.04	.03	.12	.14	6 (AKP/o.)
Güneş	AKP-Leaning	.77	.06	.01	.02	.15	.03	15 (AKP/o.)
Habertürk	AKP-Leaning	.33	.21	.07	.03	.36	.51	2,7 (AKP/o.)
İstiklal	AKP-Leaning	.36	.21	.03	.02	.38	.08	2,2 (AKP/o.)

**Table 9 (Continued)**

Karar	AKP- Leaning	.32	.29	.04	.03	.32	.02	1,3 (AKP/o.)
Milli Gazete	AKP- Leaning	.41	.27	.02	.05	.26	.02	1,8 (AKP/o.)
Milliyet	AKP- Leaning	.31	.24	.07	.03	.35	.37	1,6 (AKP/o.)
Yeni Birlik	AKP- Leaning	.06	.24	.01	.01	.69	.01	0,4 (AKP/o.)
ABC	CHP	.05	.72	.10	.02	.10	.03	5,7 (CHP/o.)
Aydınlık	CHP	.12	.68	.04	.03	.13	.09	5,5 (CHP/o.)
Cumhuriyet	CHP	.14	.46	.09	.02	.29	.41	5,2 (CHP/o.)
Gazeteport	CHP	.14	.60	.06	.03	.17	.01	3,5 (CHP/o.)
Gerçek- Gündem	CHP	.11	.68	.07	.03	.11	.04	4,6 (CHP/o.)
Grihat	CHP	.10	.62	.09	.04	.14	.02	3,5 (CHP/o.)
Odatv	CHP	.13	.61	.06	.03	.18	.24	6,3 (CHP/o.)
Sol Haber- Portalı	CHP	.10	.55	.16	.02	.17	.17	3,4 (CHP/o.)
Sözcü	CHP	.13	.56	.04	.03	.24	.32	8 (CHP/o.)
Yeni Asya	CHP	.14	.62	.03	.04	.17	.01	3,9 (CHP/o.)
Yön Haber	CHP	.06	.65	.16	.02	.11	.01	3,7 (CHP/o.)
Yurt	CHP	.11	.70	.06	.03	.10	.06	5,3 (CHP/o.)
Artı Gerçek	HDP	.04	.46	.39	.01	.10	.02	5,9 (HDP/o.)
Bianet	HDP	.09	.41	.33	.01	.16	.06	5,8 (HDP/o.)
Birgün	HDP	.12	.47	.18	.02	.22	.24	3,3 (HDP/o.)
Diken	HDP	.13	.47	.19	.02	.21	.17	3 (HDP/o.)
Dokuz8- Haber	HDP	.06	.52	.28	.01	.14	.03	3,6 (HDP/o.)

**Table 9 (Continued)**

Evrensel	HDP	.09	.41	.36	.01	.13	.11	8,9 (HDP/o.)
Gazete-Duvar	HDP	.08	.46	.33	.01	.12	.03	4,8 (HDP/o.)
T24	HDP	.20	.37	.17	.02	.24	.22	3 (HDP/o.)
Etikhaber	MHP	.07	.08	.01	.73	.10	.01	118 (MHP/o.)
Gazete-2023	MHP	.10	.28	.01	.46	.15	.01	28 (MHP/o.)
Ortadoğu	MHP	.11	.19	.01	.56	.13	.02	69 (MHP/o.)
Ülkücü-Medya	MHP	.34	.19	.01	.26	.20	.04	15 (MHP/o.)
Yeniçağ	MHP	.10	.49	.01	.23	.17	.01	9 (MHP/o.)
Gazeteciler	Centrist	.32	.38	.08	.04	.17	.02	n-a
Haberler	Centrist	.32	.34	.08	.05	.22	.02	n-a
Hürriyet	Centrist	.25	.28	.06	.03	.38	.56	n-a
Medyafaresi	Centrist	.28	.43	.04	.04	.21	.03	n-a
Medyaradar	Centrist	.37	.36	.04	.04	.19	.01	n-a
Türk Time	Centrist	.43	.14	.01	.02	.39	.01	n-a

**Note.** The column “Cluster” points to partisan media clusters in which news outlets take place based on their co-subscribers on Twitter. The column “Share” refers to the proportion of an outlet’s total number of followers in the sample to the all followers in the sample (n=2.790.339). The column “Odds Ratio” illustrates how likely an average pro-party user (identified inside the parenthesis) to follow an outlet compared to other three parties’ supporters which is abbreviated as “.../o.” and means “.../others” inside the paranthesis.

Table 9 demonstrates that, news outlets on Twitter dominantly attract audience that share their political views. For example, 78% of followers of Yeni Akit Newspaper (which is classified as pro-AKP based on its co-subscribers) are identified as pro-AKP. Similarly, 56% of pro-CHP Sözcü newspaper followers comprise Twitter users who are identified as pro-CHP. Table 9 shows that without any exception, all newspapers that are classified as pro-AKP and pro-CHP have a dominant follower proportion from that party, which is a clear evidence of attracting partisan

selective exposure. On the other hand, the news outlets that are classified as centrist have fairly balanced follower proportions especially from pro-AKP and pro-CHP Twitter users. For example, Hurriyet newspaper, which has a follower share of 56% among all the sample, comprises 25% of pro-AKP and 28% of pro-CHP followers.

However, as Table 9 shows, some of the news outlets that are classified as pro-HDP and pro-MHP attract more out-party followers than their corresponding party supporters. For example, when looking at Birgün newspaper which is classified as pro-HDP, it attracts 47% of the pro-CHP Twitter users, while attracting only 18% of pro-HDP audience, which is nearly three times lower than pro-CHP users.

At first glance, this might cast a doubt on the classification of pro-HDP news outlets, as they have more pro-CHP followers than pro-HDP followers. However, for each party-associated media cluster, a) the number of the member outlets, b) the sample size of party-associated Twitter users and c) outlets' number of followers greatly differ, which might influence the proportions. Therefore, odds ratio statistics, which is used to evaluate whether the odds of a certain outcome are the same or more likely for two different groups (Bland & Altman, 2000), are also included into the Table 9<sup>9</sup>. The values in odds ratio statistics column refers to the ratio of probability that a pro-party audience on average will follow a like-minded outlet versus the probability that other party audiences on average will follow that cross-ideological outlet. An odds ratio greater than 1 refers to a positive relationship such that greater that ratio, greater the odds that a pro-party Twitter user follows like-minded news outlet compared to out-party audience. An odds ratio lower than 1 means less likelihood for a pro-party

---

<sup>9</sup> See for the explanation and calculation of odds ratio statistics in website: [www.statisticshowto.com/odds-ratio/](http://www.statisticshowto.com/odds-ratio/)

Twitter user to follow like-minded news outlet compared to out-party followers.

These ratios in Table 9 clearly show that, for all pro-HDP news outlets, an average Twitter user who is identified as pro-HDP is at least 3 times more likely to follow pro-HDP outlets than the audience who are not identified as pro-HDP. As a specific example, pro-HDP audience are 1,7 times more likely than pro-CHP audience to follow Birgün newspaper on Twitter. However, the likelihood for pro-CHP audience to follow Birgün compared to pro-HDP audience is less than 1 (0,5), meaning that pro-HDP Birgün attracts more HDP partisans than that of CHP.

The odds ratio statistics give similar yet stronger results for pro-MHP users toward MHP-associated outlets. For example, while *ülkümedya.com* which is coded as pro-MHP attracts more AKP partisans in proportions (34%) than pro-MHP followers (26%), the odds ratio statistic reveals that an average pro-MHP Twitter user is 10 times more likely to follow *ülkümedya* compared to an average pro-AKP user on Twitter. Likewise, an average MHP supporter is 5 times more likely to follow pro-MHP *Yeniçağ* newspaper compared to supporters of CHP.

As Table 9 shows, without any exception, all pro-party Twitter audiences are more likely to follow news outlets that share their political predispositions, which is a clear evidence of partisanship in Turkish media system. However, it is not clear whether some outlets go beyond this partisanship in terms of attracting more partisans. To investigate this question, an additional variable is added to Table 9. The column “share” gives the fraction of followers of a newspaper to the all sample population (n= 2.790.339). For example, the share of *Akşam* newspaper, (which has a total of 411.265 followers in the sample) to the whole follower population is

0.15 (411.265/2.790.339). These share numbers illustrate how popular a news outlet among the sample follower population. To investigate whether “niche outlets” that have a very low share of followers attract more partisans compared to more mainstream outlets having a large share, a correlation analysis between outlets’ share and follower numbers is performed. The correlation value is very low, ( $r = -.248$ ), showing that there is not a statistically meaningful relationship between outlets’ popularity and their attraction of partisanship. For example, “print” Sabah newspaper, which has a share of .28 in the sample, and “digital-only” internethaber.com, which has a share of only .04 in the sample, have nearly the same proportions (.48 and .46 respectively), in terms of attracting pro-AKP Twitter audience. Consequently, no matter how popular or “niche” in terms of their follower population, all news outlets that are clustered within a political party attract audience that exercise partisan selective exposure.

## **5.2. Polarization**

As explained in Methodology chapter, this thesis measures political polarization by taking into consideration the distance between congenial and uncongenial political party/deputy accounts followed on Twitter. Furthermore, to strengthen and validate this measurement, a second polarization index, “retweet polarization” is also used.

Before proceeding to the main hypothesis of this thesis regarding the relationship between partisan selective exposure and polarization, it would be useful to investigate whether and to what extent is there a political polarization in Turkish Twitter users. Table 10 shows the polarization indices for both political and retweet polarization measurements based on party identification and partisanship strength.



**Table 10***Polarization Indices Based on Political and Retweet Polarization on Twitter*

Political Identification		Descriptive Statistics					
		Political Polarization			Retweet Polarization		
Party Id	Id Strength	Mean	S.D.	N	Mean	S.D.	N
AKP	strong	0,70	0,17	5313	87,28	25,30	5313
	moderate	0,50	0,12	5317	80,48	31,08	5317
	weak	0,32	0,07	1576	73,42	35,86	1576
	leaned	0,25	0,00	310	68,87	38,51	310
	Total	0,55	0,19	12516	82,19	30,11	12516
MHP	strong	0,75	0,22	741	64,67	32,97	741
	moderate	0,63	0,18	661	56,61	34,60	661
	weak	0,45	0,11	509	59,80	33,90	509
	leaned	0,44	0,00	130	57,81	34,59	130
	Total	0,62	0,22	2041	60,41	33,99	2041
CHP	strong	0,69	0,19	4276	83,68	23,02	4276
	moderate	0,53	0,12	4495	83,76	24,76	4495
	weak	0,40	0,07	2739	80,98	28,71	2739
	leaned	0,33	0,00	1260	82,35	28,42	1260
	Total	0,54	0,19	12770	83,00	25,51	12770
HDP	strong	0,68	0,16	867	93,33	18,87	867
	moderate	0,49	0,12	1039	88,78	24,75	1039
	weak	0,36	0,07	510	86,65	25,95	510
	leaned	0,30	0,00	195	85,60	27,45	195
	Total	0,51	0,18	2611	89,64	23,60	2611
Mixed	mixed	0,18	0,10	5828	70,98	36,20	5828
Total	strong	0,70	0,18	11197	84,88	25,32	11197
	moderate	0,52	0,13	11512	81,14	29,19	11512
	weak	0,38	0,09	5334	77,27	32,03	5334
	leaned	0,32	0,04	1895	78,80	31,57	1895
	mixed	0,18	0,10	5828	70,98	36,20	5828
	Total	0,49	0,23	35766	79,95	30,27	35766

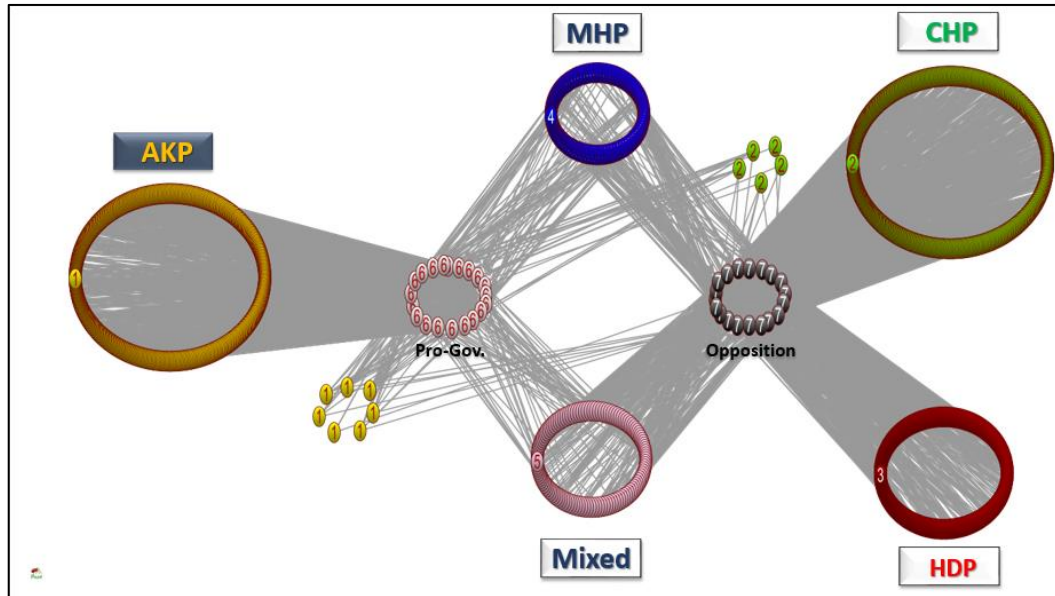
**Note.** “Leaned” users in the table have a standard deviation value of zero as they consist of users who follow exactly 3 deputies from their favored party.

As Table 10 clearly shows, there is a deep polarization among Turkish Twitter users who follow political news outlets and politicians on Twitter. Moreover, this polarization level is much higher for people who

have strong political affiliations with their favored political parties. In other words, as strength of party identification level increases, so does the level of polarization, which can be seen both in political party following and retweeting patterns. Likewise, as strength of affiliation with a political party decreases, so does the level of polarization. These results imply that, irrespective of the favored political party, strength of partisanship is a significant indicator of political polarization.

It might be argued that the level of retweet polarization for pro-MHP Twitter audience on Table 10 is different (lower) when compared to other pro-party users. In particular, while all other parties' strong partisans have polarization indices higher than 80, pro-MHP audience with a strong party affiliation have a polarization index of 64. This finding has a significant implication. As retweet polarization is measured by categorizing retweeted accounts as either pro-government or oppositional, low levels of pro-MHP polarization in favor of the ruling party shows a "being stuck" situation. In other words, this finding implicates that although still faithful to their political party and to most of its deputies, some of the voters of MHP might be reluctant in following their political leader Devlet Bahçeli in terms of supporting the government and having tight political bonds with the ruling AKP.

To illustrate political polarization visually, random sample of 1200 users including all four political party supporters as well as politically mixed users are selected. Afterwards, their retweet links to the most retweeted 20 left-leaning and 20 right-leaning Twitter accounts are investigated. The output is shown in Figure 4.



**Figure 4.** Retweet Polarization of Pro-party and Politically Mixed Twitter Users. The number of network clusters from 1 to 5 represent pro-AKP (yellow), pro-CHP (green), pro-HDP (red), pro-MHP (blue), and politically mixed (pink) Twitter audience respectively. Cluster numbers of 6 and 7 represent most retweeted 20 pro-government (white) and 20 oppositional (black) Twitter accounts respectively. Each link goes from pro-party and mixed users to pro-government and oppositional accounts and represents a retweet relationship between them. For a better visualization, a link is created between a user and an account only if that account is retweeted at least 5 times by that user.

Figure 4 illustrates a clear polarization among pro-AKP, pro-CHP and pro-HDP partisans in terms of retweeting the most popular 40 pro-government and oppositional Twitter accounts. The network analysis shows that Turkish Twitter users are very unlikely to retweet cross-ideological accounts on Twitter. The five green nodes labeled as “2” in the upper right side of the network represent pro-CHP users who have retweet links to pro-government accounts. Similarly, the 7 yellow nodes labeled as “1” in the lower left side of the network represent pro-AKP users who have retweet links to oppositional accounts. In particular, only 7 out of 377 pro-AKP sample retweets oppositional accounts. Likewise, only 5 out of 397 pro-CHP sample retweets pro-government accounts. Interestingly, there is

not a single user out of 166 pro-HDP sample that retweets pro-government accounts. These findings show that the supporters of AKP, CHP and HDP take a firm stand on their political position as being either adherent or opponent to the ruling party. However, although the MHP is ideologically left-wing like the ruling AKP and the leader cadre has announced their decision to form a political alliance with the ruling party, Figure 4 shows that pro-MHP Twitter audience seems to be confused and indecisive about their support to the government. Combining with the political polarization results given in Table 10, it can be said that pro-MHP users are polarized in terms of following their deputies which represent their political party, but not polarized in terms of following their leader's decision to affiliate with AKP. On the other hand, that more retweet links from mixed users go to oppositional accounts compared to pro-government accounts might imply that Turkish Twitter population represents more left-leaning and oppositional audience compared to pro-government users.

### 5.3. Partisan Selective Exposure and Polarization

The twitter data used in this study yielded a clear evidence of partisan selective exposure and political polarization. But the main research question of this thesis is whether partisan selective exposure levels affect and predict political polarization. The results of the regression analysis with interaction terms are illustrated in Table 11.

**Table 11**

*Regression Analysis Predicting Political Polarization*

<u>Control Variables</u>	$\beta$	t
Twitter Use Frequency	.005	1,6
Political Discussion	.006	1,6
Political Interest	.102***	26,4
<u>Main Effects</u>		
Partisanship(AKP)	.295***	57

**Table 11 (Continued)**

Partisanship(CHP)	.358***	73
Partisanship(HDP)	-.160***	-26,6
Partisanship(MHP)	-.160***	-33,3
Selective exposure (AKP)	-.283***	-30,3
Selective exposure (CHP)	-.104***	-14,5
Selective exposure (HDP)	-.080***	-13,4
Selective exposure (MHP)	-.047***	-7
<u>Interactions</u>		
<b>Interaction (S.E._AKP * Prt_AKP)</b>	<b>.137***</b>	<b>18,4</b>
Interaction (S.E._CHP * Prt_AKP)	-.239***	-37,2
Interaction (S.E._HDP * Prt_AKP)	-.139***	-24,7
Interaction (S.E._MHP * Prt_AKP)	-.127***	-25,9
Interaction (S.E._AKP * Prt_CHP)	-.289***	-37,1
<b>Interaction (S.E._CHP * Prt_CHP)</b>	<b>.143***</b>	<b>23,5</b>
Interaction (S.E._HDP * Prt_CHP)	-.091***	-20,4
Interaction (S.E._MHP * Prt_CHP)	-.139***	-26,2
Interaction (S.E._AKP * Prt_HDP)	-.068***	-8,1
Interaction (S.E._CHP * Prt_HDP)	-.074***	-14,0
<b>Interaction (S.E._HDP * Prt_HDP)</b>	<b>.193***</b>	<b>24,7</b>
Interaction (S.E._MHP * Prt_HDP)	-.048***	-8,3
Interaction (S.E._AKP * Prt_MHP)	-.108***	-14,7
Interaction (S.E._CHP * Prt_MHP)	-.114***	-15,8
Interaction (S.E._HDP * Prt_MHP)	-.047***	-8,4
<b>Interaction (S.E._MHP * Prt_MHP)</b>	<b>.179***</b>	<b>19,0</b>
Total R <sup>2</sup>	.626	
N	35766	

**Note.** Dependent Variable: Political Polarization. Cell entries represent standardized coefficients from multiple regression analysis with interaction terms. “S.E.\_party” represents pro-party selective exposure. “Prt\_party” denotes for the partisanship level of pro-party audience. “S.E.\_party \* Prt\_party” shows the the interaction term between selectivity and partisanship toward parties. Twitter users who are identified as moderate/mixed were excluded from the model in accordance with the operational definition of partisan selective exposure. \*p < .05. \*\*p < .01. \*\*\*p < .001.

The multiple regression analysis in Table 11 clearly shows that the interactions between partisanship and pro-party media exposure is statistically significant in predicting political polarization. Moreover, these interactions are significant even in the presence of the control variables. The results of the analysis support the hypotheses in that for all political party supporters, partisan selective exposure to like-minded news outlets is

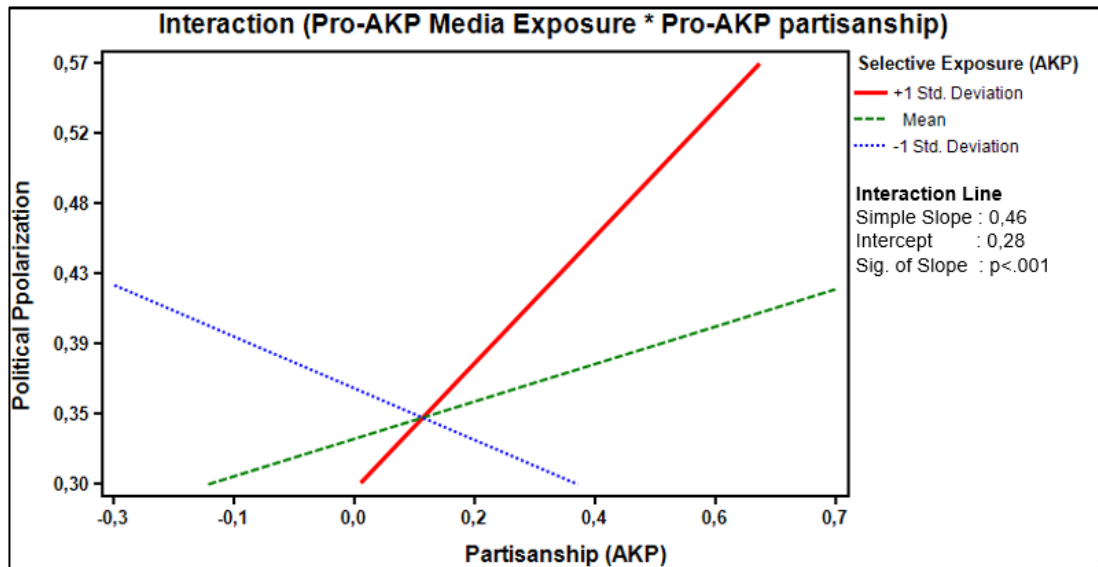
positively associated with political polarization. More specifically, pro-party users following more politically congenial news outlets on Twitter possess more polarized attitudes relative to other pro-party users. On the other hand, pro-party users following more uncongenial news outlets on Twitter possess less polarized attitudes relative to other pro-party users.

In sum, the interactions reveal that, whatever the favored party, stronger partisanship combined with corresponding political media exposure leads to political polarization. The analysis also reveals that, no matter how strong the partisanship strength for a party is, consuming less like-minded and more cross-cutting political information on Twitter leads to lower levels of political polarization compared to consuming higher levels of partisan selective exposure.

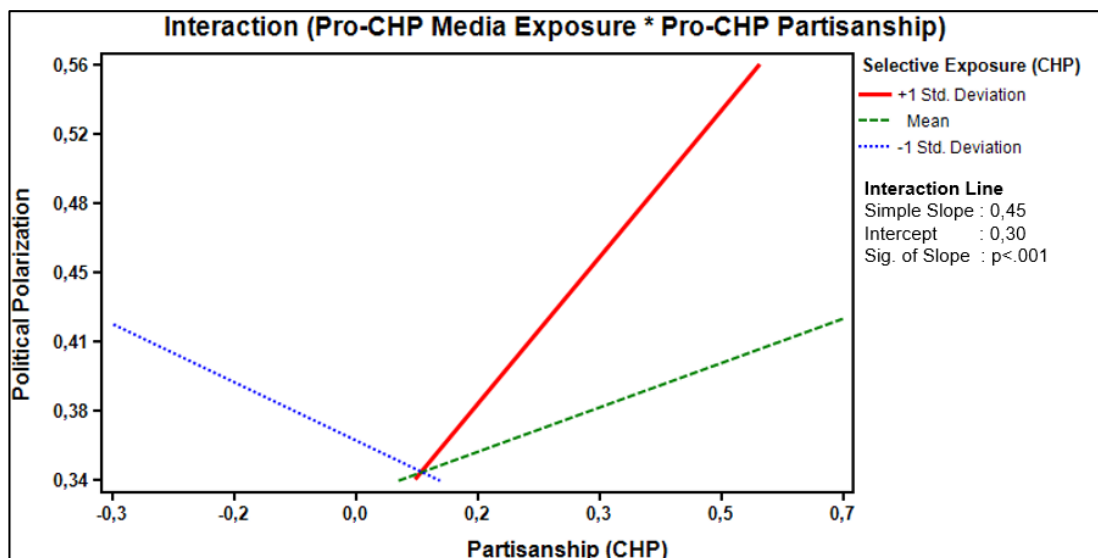
On the other hand, the control variable, political interest and the main effect, partisanship are also significant ( $p < .001$  for both) in terms of predicting political polarization. These findings show that politically more interested audience are more likely to become polarized compared to politically less-interested Twitter audience. Likewise, no matter which party it is, having a strong party identification is associated with political polarization.

The interaction between pro-party media exposure and partisanship level on political polarization is plotted for each party in Figure 5, 6, 7, and 8. All these interactions show a weak to high steep slope for the selective news exposure on Twitter, meaning that Twitter users who exercise higher levels of like-minded news exposure showed higher levels of political polarization when they have stronger party identification compared with those who have lower levels of like-minded news exposure. On the other hand, that the slope of the interaction lines for Figure 5 and Figure 6 are

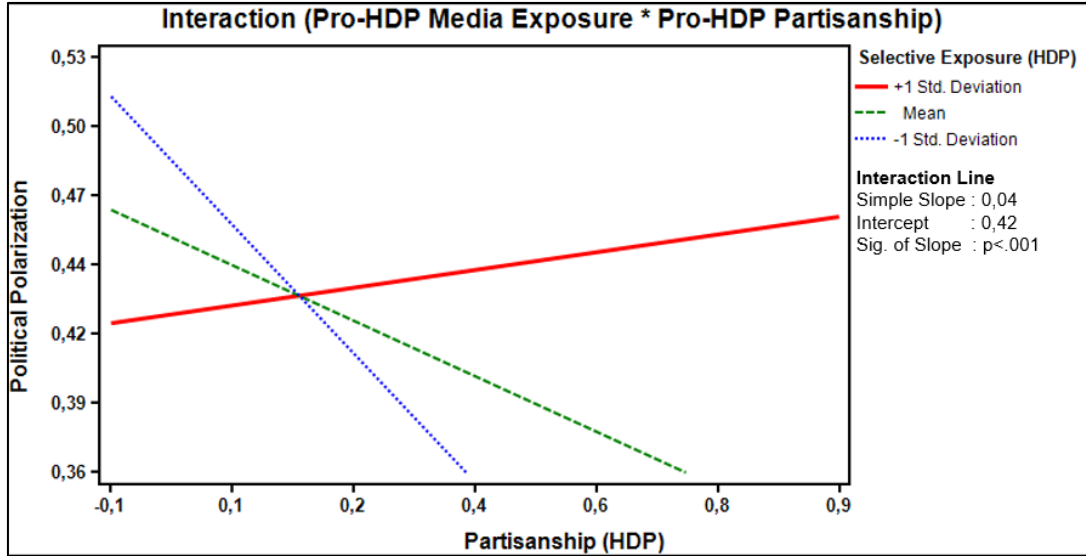
steeper compared to lines in other two figures demonstrate that pro-AKP and pro-CHP news exposure on Twitter is more associated with political polarization compared to selective news exposure that is in favor of HDP and MHP affiliated news outlets.



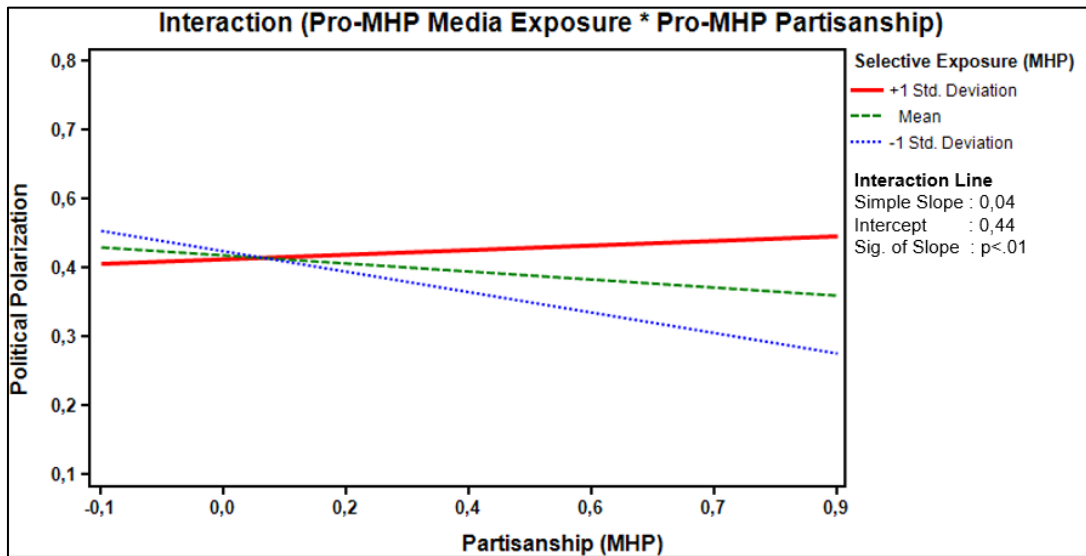
**Figure 5.** Interaction between pro-AKP news exposure and partisanship on polarization.



**Figure 6.** Interaction between pro-CHP news exposure and partisanship on polarization.



**Figure 7.** Interaction between pro-HDP news exposure and partisanship on polarization.



**Figure 8.** Interaction between pro-MHP news exposure and partisanship on polarization.

#### 5.4. Assessing the Validity of Polarization and Partisanship Measures

In order to assess the validity of the polarization measure that is used in this thesis, the same interactions and the controls are re-tested by using the retweet polarization index as the dependent variable. As this index



evaluates polarization based on pro-government and oppositional positions instead of capturing polarization in terms of party-affiliations, two political parties, AKP and CHP, which best represent these ideological poles are selected for the regression analysis. As Table 12 shows, the interaction between partisan news outlet consumption and ideological identification is also statistically significant in predicting polarization based on retweets. Especially for supporters of AKP and CHP, the analysis reveals that Twitter users with a strong party identification who consume like-minded news outlets will show more polarized political attitudes than users with a strong party identification who don't consume like-minded news outlets that much.

**Table 12**

*Regression Analyses Predicting Retweet Polarization*

<u>Control Variables</u>	<b><math>\beta</math></b>	<b>t</b>
Twitter Use Frequency	-.008	-1,3
Political Discussion	.059***	9,2
Political Interest	.113***	16,9
<u>Main Effects</u>		
Partisanship(AKP)	-.011	-1,2
Partisanship(CHP)	-.159***	-17,7
Selective exposure (AKP)	.061***	4,3
Selective exposure (CHP)	.075***	6,5
<u>Interactions</u>		
<b>Interaction (S.E._AKP * Prt_AKP)</b>	<b>.132***</b>	<b>7,9</b>
Interaction (S.E._CHP * Prt_AKP)	-.066***	-5,3
Interaction (S.E._HDP * Prt_AKP)	-.018*	-2,0
Interaction (S.E._MHP * Prt_AKP)	.015	1,6
Interaction (S.E._AKP * Prt_CHP)	-.044**	-3,0
<b>Interaction (S.E._CHP * Prt_CHP)</b>	<b>.065***</b>	<b>5,3</b>
Interaction (S.E._HDP * Prt_CHP)	-.006	-0,7
Interaction (S.E._MHP * Prt_CHP)	-.037	-4,1
Total $R^2$	.147	
<i>N</i>	24545	

**Note.** Dependent Variable: Retweet Polarization. Cell entries represent standardized coefficients from multiple regression analysis with interaction terms. "S.E.\_party" represents pro-party selective exposure. "Prt\_party"

denotes for the partisanship level of pro-party audience. “S.E.\_party \* Prt\_party” shows the the interaction term between selectivity and partisanship toward parties. Twitter users who are identified as moderate/mixed were excluded from the model in accordance with the operational definition of partisan selective exposure. \* $p < .05$ . \*\* $p < .01$ . \*\*\* $p < .001$ .

These results are highly consistent with that of Table 11 which measures polarization based on following pro-party deputies on Twitter. Consequently, there is enough evidence that in both measurement strategies, partisan selective exposure is related to higher levels of polarization. Moreover, except for interaction between pro-AKP users’ MHP-affiliated news outlet consumption, all other cross-ideological interactions are negatively and at least marginally significant, meaning that uncongenial media consumption is related to lower levels of polarization. In sum, this regression analysis in which retweet polarization index is used as the dependent variable yields highly consistent interaction results with the previous analysis in which political polarization index is used as the dependent variable. Accordingly, it can be put forward that the polarization measurement used in this thesis is a valid estimation of the polarized political attitudes of Turkish Twitter users who follow political accounts and news outlets on Twitter.

On the other hand, the alternative measurement of the partisanship also verifies the validation of the primary measurement that captures partisan leanings of Twitter users in this study. Table 13 illustrates the results of the alternative partisanship measurement in comparison with the primary partisanship classification.

The comparison in Table 13 reveals that, there is a strong consistency between these two partisanship measurements. 93% of Twitter audience that have a strong identification with AKP frames that party as “akparti” in their tweets, whereas only 7% of them mostly uses “akp” when mentioning

about that party in their tweets. Similarly, 93% and 97% of Twitter audience that have a strong identification with CHP and HDP respectively frames the ruling party as “akp” in their tweets, while only 7% and 3% of them respectively uses “akparti” when tweeting about it.

**Table 13**

*Comparison of the Partisanship Measurements*

Political ID	Id_strength	% of users who dominantly frame the ruling party as;	
		"akparti"	"akp"
AKP	strong_AKP	93	7
	moderate_AKP	84	16
	weak_AKP	72	28
	leaned_AKP	70	30
CHP	strong_CHP	7	93
	moderate_CHP	7	93
	weak_CHP	8	92
	leaned_CHP	9	91
HDP	strong_HDP	3	97
	moderate_HDP	5	95
	weak_HDP	10	90
	leaned_HDP	5	95
MHP	strong_MHP	18	82
	moderate_MHP	19	81
	weak_MHP	25	75
	leaned_MHP	14	86

In particular, following AKP deputies on Twitter is a strong indicator of framing that party as “akparti”, which is also an indicator of support toward that party. Similarly, following oppositional parties (CHP and HDP) on Twitter is also a strong indicator of negatively framing the ruling party as “akp”. However, consistent with the primary partisanship index, following MHP deputies on Twitter is not an indicator of positively framing the ruling party as “akp”. Although still oppositional to an extent, Table 13 shows that pro-MHP Twitter audience’s opposition is not as strong as CHP and HDP. In Sum, these framing proportions which are highly consistent

with the party identifications and their strength demonstrate that the partisanship measurement used in this thesis is a valid estimation of the political party predispositions of Turkish Twitter users.

## CHAPTER 6

### DISCUSSION AND CONCLUSION

This thesis investigated partisan selective exposure, political polarization and the relationship between these two phenomena in Turkish Twitter users' context by using a novel and big data set collected from Twitter database. It first examined the concept of partisan selective exposure and polarization with a broad perspective in the literature. Secondly, it explained which strategy to choose in order to measure these concepts as well as how to analyze their statistical association.

The results of the analyses suggest that, Turkish Twitter users who consume political news on Twitter practice a very high level of partisan selective exposure. Moreover, these audiences are very polarized in terms of following only deputies that represent their political parties as well as retweeting accounts that represent only their own political views. Irrespective of the political party that is favored, strength of party identification is found to be closely related to this high level of partisan selective exposure and polarization. Conversely, weak identification with a party is found to be a strong indicator of cross-cutting news exposure and lower levels of polarization. Taken together, the results show that Turkish Twitter users are highly biased and polarized in favor of their existing political predispositions when consuming political news and when following political accounts on Twitter. Given that the data collection period of this study doesn't coincide with the upcoming presidential and

mayoral election period which will occur in 2019, the results of this thesis suggest that the polarization is likely to increase in the next two years.

While illustrating a strong tendency for partisanship in Turkish Twitter networks, the results of this thesis also shows that most of the media sources that are investigated in this study are aligned with and represent a specific political party or ideology. Moreover, the results also affirm that political news outlets that have an account on Twitter, *be it niche or mainstream, digital-only or print, popular or unpopular*, almost equally appeal like-minded partisans on Twitter. More specifically, there is not a single news outlet that is clustered within a party-associated media cluster which has more followers from oppositional parties. These results illustrated in Table 9 shows that news outlets with a political affiliation attract disproportionate numbers of like-minded followers. These outputs imply a very low level of internal pluralism at the news outlet level, as well as a very high level of external pluralism at the level of Turkish media system as a whole. In the light of the results, it can be said that internet and online media sources are far away from mobilizing audience to politically diverse and balanced information. Concludingly, instead of being an alternative to the traditional and mainstream news sources in terms of reporting objective and politically balanced news, most of the digital-only news outlets seems to be an imitation of the existing traditional media. However, whether these media sources exacerbate partisan selective exposure and polarization by reinforcing existing political prejudices should be investigated in further studies.

The analyses of this study showed that the news outlets clustered as pro-akp are dominantly attracting Twitter audience that are identified as supporters of AKP. However, the news outlets clustered as pro-CHP and

pro-HDP are mutually attracting each other's partisans. In line with the arguments of Çarkoğlu et al. (2014), these results suggest that, while the ruling AKP accumulates its media sources alone, the high fragmentation in oppositional parties restrain any oppositional party to accumulate media sources by its own. Therefore, instead of a press-party parallelism model in which each media source is aligned with a specific party, Turkey seems to have a political media system in which media sources are aligned with either the ruling AKP (pro-AKP) or with political parties and even ideologies that are opponent of AKP. In the light of these findings, the most suitable classification that would define Turkish news outlets's political predispositions seems to be pro-AKP and oppositional.

The results also support for the main hypothesis of this thesis, which suggested that partisan selective exposure predicts political polarization. Indeed, the regression analyses demonstrated that like-minded news exposure on Twitter has a significant influence on political polarization, whereas cross-cutting news exposure is related with more moderate attitudes and less level of political polarization, even after controlling for the variables of political interest, media use frequency and political discussion on Twitter. Moreover, the statistical results were consistent when measuring Twitter users' polarization based on their retweets to ideologically challenging political accounts. These findings demonstrate that, partisans consuming more like-minded and less opinion-challenging news on Twitter are more likely to become politically polarized, either by following only their own party's politicians or by retweeting only ideologically-congenial political accounts. As Sunstein (2007) notes, consuming news slanted toward audience's own political views and avoiding sources with a counter-attitudinal slant leads to an information pool which is extremely biased in favor of the pre-existing political

predispositions. Perpetually being exposed to a such an unbalanced pool of political information reinforces already existing political attitudes and eventually promotes political polarization. Likewise, from a cognitive perspective, relying merely on like-minded news might increase the feeling of enthusiasm for the supported party (Marcus, Neuman, & MacKuen, 2000), which reinforces the affective ties between a partisan and her party, and hence increase polarization. The findings of this study demonstrate that consuming politically counter-attitudinal and challenging information on Twitter is an effective way to reduce polarized attitudes. Taken together, this thesis contributes to the existing literature by providing a strong association between politically homogeneous news exposure and attitude polarization.

Given that majority of the Twitter users in Turkey practice partisan selective exposure, these findings fuel concerns about the desired democratic deliberation in Turkey where individuals would express their political views and mutually understand diverse arguements. Furthermore, considering that individuals who practice greater cross-ideological news exposure have greater tolerance, are more accessible to political discussions and understand the other side's arguments better (Diana C. Mutz, 2002, 2006).

Of the 53 news outlets, only 6 (11%) is found to be centrist and moderate compared to other 47 party-associated news outlets. Such a highly partisan media setting points to two mutually interacting implications. First, high level of partisanship in Turkey motivates media organizations to appeal to their readers' polarized attitudes by reporting highly partisan and biased political news. Second, highly partisan and biased journalism in Turkey which is visible across all political news outlets



reinforces their readers' political views and motivates them to possess more extreme and biased attitudes. The findings of this thesis show that both of these two phenomena mutually contribute to each other and gets into a vicious circle in which both media sources and its consumers motivates each other to become more partisan and polarized. In such a setting, it is very unlikely to be able to communicate, deliberate, try to understand and accept the political arguments of the "other side", which is highly essential in the progress of democratic societies. Especially, considering the modest evidence in media's activation and reinforcement effect on people's political attitudes even in media settings with a balanced journalism (Dilliplane, 2014), it is very reasonable to suggest that highly partisan media system in Turkey contributes to attitude polarization by activating and reinforcing individuals' already extreme political attitudes. Thus, some legislative regulations on Turkish media system is advised to be made by the authorities in which highly partisan and biased content with an incivil tone should be minimized and a broader and objective political perspective in reporting should be motivated. On the other hand, significant association between higher levels of counter-attitudinal news consumption and lower levels of polarization lay emphasis on the need to develop both online and offline public spheres in which people with diverse political views could communicate with each other. In sum, being exposed to politically heterogeneous media sources and communication networks seems to be one of the key remedies to reduce political polarization in Turkey.

A contribution of this study to the literature is that, to the researcher's best knowledge, this is the first study in multi-party systems to measure partisan selective exposure based on party identifications rather than a dichotomous left and right ideological division. Indeed, many studies outside the U.S. -which is a two-party system- identified the audience as left

and right leaning, as it was easier to measure and compare the results with that of U.S. However, as Garrett (2014) notes, this is a problematic approach in multi-party systems. This approach could underestimate selectivity and polarization as supporters of various political parties may possess different and even less favorable feelings toward other parties which have politically similar ideologies with their own parties. Indeed, in Turkey's multi-party system, in which different political ideologies are represented by various political parties, left-right distinction would be insufficient to measure partisanship and polarization effectively.

Another contribution of this thesis to the literature is that, it explores the relationship between partisan selective exposure and political polarization based on an original Twitter data, which is not affected from self-report bias such as social desirability and mis-recalling. As Prior (2013) notes, people are likely to over or underestimate their selective exposure to congenial and cross-ideological media news in surveys. Moreover, many past studies with surveys measure selective exposure by asking respondents a) which newspaper they read most often (Stroud, 2008, 2010), b) how often/frequently they read certain media sources that are included in the study<sup>10</sup> (Garrett et al., 2014; Gentzkow & Shapiro, 2011; Gvirsman, 2014; Johnson et al., 2009; Yonghwan Kim, 2015). The scholars use these scales to measure the level of partisan selective exposure. However, consuming like-minded news doesn't necessarily mean avoiding news that is slanted away from one's political views. A participant who consumes like-minded news very frequently can not be claimed to practice partisan selective exposure if she also consumes uncongenial news very frequently. Thus, by using a measurement which takes into consideration both pro-

---

<sup>10</sup> These frequencies range from "never" to "very frequently/very often/ every day...".

party and counter-party news exposure, this thesis makes a significant contribution to the literature. On the other hand, the data used in this thesis also overcomes the possible measurement bias that is seen in many experimental researches. In particular, the news sources (partisan and neutral) offered to subjects in experimental studies to measure their selectivity might not represent their news selection preferences in real life. Therefore, forcing to choose one of the two challenging media sources in these designs would not reflect their actual exposure preferences, and consequently would lead to misleading results. In this thesis, exposure and polarization measures are based on a big and objective Twitter data, which makes the results of this thesis very valuable both in global and national political contexts.

One major limitation of this thesis is that the dataset used in this study is a cross-sectional snapshot which captures a large Twitter sample at a single point in 2018. As it is not an experimental study, regression models used in this study can not establish causal direction. Although past longitudinal studies in other countries demonstrate that partisan selective exposure leads to polarization instead of vice versa (Garrett et al., 2014; Stroud, 2010), in Turkish Twitter context a reverse causality is possible and can not be ruled out. Thus, further studies would use an experimental data or a cross-lagged panel design to clarify the causal direction between partisan selective exposure and polarization in Turkey.

This thesis collected data from Twitter users who followed political news outlets and political accounts to examine the relationship between partisan selective exposure and polarization. However, there might be some “read-only” Twitter users who got information from news outlet and political entities without subscribing to these accounts. Therefore, further

studies should examine whether these “read-only” users exercise partisan selective or cross-ideological exposure on Twitter. Moreover, following a Twitter account does not necessarily mean that all of its tweets (political messages and news) will be read on Twitter. The assumption that the tweets of an account are all exposed by its subscribers might lead to misleading conclusions both for selective news exposure and political polarization. Thus, future research should investigate whether and to what extent the tweets of a Twitter account are read by their followers. On the other hand, the political keywords and hashtags that are selected to create “political interest” and “political discussion” variables for investigating the pure effect of partisan selective exposure on polarization are not representative of the all political words and hashtags used in Twitter political content. There might be some other keywords and hashtags referring to political interest and political discussion, which should be captured in further studies.

On the other hand, this study examines direct selective exposure to like-minded political information, as well as its relationship with polarization. However, some exceptional studies suggest that a great amount of Twitter users (between 60-98%) who exercise partisan selective exposure to like-minded political information are indirectly exposed to cross-ideological information on Twitter, either by their friends who follow politically dissimilar accounts or by cross-cutting mentions, replies or retweets that appear on their Twitter timeline and notification tabs (An, Cha, Gummadi, & Crowcroft, 2011). Future studies could also account for the exposure to politically heterogeneous communication networks and indirect exposure when investigating selectivity and polarization.

Another limitation of this study is that the analyses and results based on a digital trace data (Twitter) carry the potential limitations due to the two central fallacies. The first fallacy about digital trace data is n=all fallacy (Mayer-Schönberger & Cukier, 2014). This study collects all the Twitter users who follow 53 political news outlets and political deputies that are representatives of four major political parties. Therefore, at first sight, the data collected in this thesis might seem to capture the whole population (n=all) that is aimed to be investigated. However, this assumption is challenged by the data access policies of Twitter which might offer the researchers a restricted and uncomplete part of the whole dataset. Therefore, “n=all” assumption might actually be the optimistic cover of the “n= a big sample representing an unknown population with unknown properties which is determined by the policies of Twitter” (Jungherr, 2019). Moreover, this is a found data, which ties the researchers’ hands by the data collection and access policies of Twitter in terms of possessing every required data type for their research questions and identifying the data collection process according to their theoretical research design. Instead, this situation forces the researchers to adjust their research design to the Twitter data which is publicly available (Howison, Wiggins, & Crowston, 2011). Indeed, demographic variables which is not provided due to the policies of Twitter casts a major problem for making a reliable and representative inference from the results of this study. Furthermore, there is no available data about the effect of the commercial and algorithmic interventions of Twitter to its audience (Jungherr, 2019). Therefore, whether the partisanship, selective exposure and polarization levels measured in this study reflects users’ real political attitudes or the effects of this intervention is not clear. Moreover, collecting all publicly available interactions among Twitter users doesn’t necessarily mean to collect all

political communication practices of those users. Considering that people would use various political communication tools such as e-mail, facebook, instagram, Linked-in, Tumblr simultaneously, and as whole political communication and interaction chain comprises all these platforms (Rainie & Wellman, 2014), capturing political attitudes from only one piece of those tools would carry the potential to drive into different and inaccurate assessments about their attitudes.

The second fallacy about digital trace data is the “mirror fallacy”, which points to the erroneous assumption that political signals such as online interactions (following, being followed, retweeting, replying etc) gathered from digital tracking data measures and mirrors the phenomena of interest such as the political attitudes of the real world (Jungherr, 2019). As Jungherr (2019) notes, patterns identified on Twitter and statistical correlations based on the big data derived from Twitter might not directly express the underlying political phenomena and might not successfully indicate micro-level public attitudes such as partisan selective exposure and polarization.

This mirror fallacy also points to the external validity problem of this study. Regression analyses that predict the magnitude of partisan selective exposure effect on political polarization lack some demographic variables such as gender, income, education, age and geographical location. Although Zhang (2009) notes that demographic variables (age, gender, income and education) accounts for the smallest variance (1.2%)<sup>11</sup> in predicting selective exposure to like-minded web-blogs compared with other blocks of variables, the models used without demographic variables in

---

<sup>11</sup> Block 1: political discussion, block 2: reliance on media sources, block 3: political variables (political interest, strength of partisanship, ideology, political participation, tolerance, and political knowledge).

this thesis casts some doubts on the generalization of the sample to the whole population especially in the context of Turkish political system. Moreover, as Twitter has a skewed user base (Jungherr, 2019), the sample used in this study is far from representing all Turkish society. Twitter population is younger, more educated, better in income (A. Smith & Rainie, 2010) and more politically interested (Bode & Dalrymple, 2014). As Garrett (2006) and Chaffe and Milyo (1983) separately notes, males and younger people (adolescences) might be more likely to practice partisan selective exposure compared to females, which implies that the findings of this study showing high level of partisan selective exposure, polarization and a significant association between these two should be held with caution regarding female and older population. Likewise, the possibility that lower socio-economic conditions – *which is also missing in this thesis's control variables* – is responsible for both partisan selective exposure and polarization cannot be ruled out. It should also be noted that as of 2016, 30% of Turkish people use Twitter as a means of consuming news (Newman et al., 2016). Accordingly, the opinions on Twitter might not accurately represent the Turkish public opinion. As the sample is not representative of the whole Turkish society, the effects of partisan selective exposure on polarization observed in this study might be limited to a large but specific and *niche* fraction of the population. Thus, any generalization of the findings of this thesis to the Turkish society would be held with caution.

There are many studies showing that online Twitter data about politics significantly mirrors the offline political behavior. Dunbar and his colleagues demonstrate that online communities on Twitter have very similar structural characteristics compared to offline face-to-face communities (Dunbar, Arnaboldi, Conti, & Passarella, 2015). Tumasjan et al. (2010) revealed that the mere number of Twitter messages which

mentions a political party successfully predicts the election results. They also revealed that joint mentions of two German political parties on Twitter strongly corresponds to the existing German political coalitions (Andranik Tumasjan et al., 2010). Likewise, Barberá shows that political communication on Twitter strongly represents offline political landscape. More specifically, he notes that the ideological positions of politicians in U.S. can be strongly estimated just by investigating their following ties with their followers (Barberá, 2015). Morales et al. (2015) shows that polarization measured on Twitter significantly predicts the territorial, social and political polarization in the Venezuelan society. From the perspectives of these scholars, even if Twitter data cannot be directly generalized to offline political populations, there are nonetheless good reasons to suggest that Twitter networks is an effective platform to investigate Turkish media and political system. Especially, when considering that our target population is politically interested Turkish people who consume political news, the big data derived from Twitter is thought to give enough evidence for inferring about partisan selective exposure, political attitudes and their level of extremism in Turkey. However, those methods which statistically link the public communication and interactions on Twitter with the real political phenomena is much criticized as these methods fall into the mirror fallacy by not testing the possible mechanisms which might lead to the emergence of those associations (see e.g., Gerring, 2010; Jungherr, Schoen, Posegga, & Jürgens, 2016). Indeed, the Twitter data used in this thesis is a big data which carry the risk to significantly associate variables that are normally not correlated. Therefore, whether the findings of this study stem from the spurious correlations among party-identifications, political news selectivity and polarization, or they mirror the real phenomena of partisan selective



exposure and its association with polarization should further investigated with other measurement strategies and smaller offline data sets.

This study measures political polarization based on following links to political party and political accounts on Twitter. It uses those links as an indicator of party-based polarization. On the other hand, it uses retweet links to pro-government and oppositional political accounts to validate the polarization measurement. Further studies could investigate polarization based on specific ideological lines, which might yield different and more comprehensive results. For example, political Islamism, conservatism, Turkish and Kurdish nationalism, Kemalism, social democracy, liberalism, feminism, socialism, communism and Marxism would be significant indicators of ideological polarization in Turkish political landscape. Likewise, ideological association rather than party-association in media sources might give more insightful results as there are many outlets that are not supporters of a specific party but shares the same ideology with that party. For example, the readers of *Milli Gazete* and *Yeni Asya*, which are clustered as AKP-leaning and pro-CHP respectively in this thesis, are ideologically conservative but not associated with the ruling AKP. Moreover, although basically being conservative, they represent different ideologies (*milli görüş* and *Nurculuk*). Thus, future studies with ideology-based media clustering would capture these newspapers which play a key role in understanding political life in Turkey.

This thesis measures polarization based on partisanship and retweet patterns. As another indicator of polarization, positive and negative affects toward media outlets and political entities could be investigated in further studies. Considering that affective polarization is significantly correlated with incivility, defamation and intolerance (Garrett et al., 2014), further

studies could research the political sentiments of Turkish Twitter users with text-mining, as well as its relationship with partisan selective exposure and polarization.

Although the findings of this study suggest that selective exposure to political news outlets on Twitter leads to political polarization, different and challenging results are possible to emerge when other media sources such as TV channels-programs, radio shows, political websites and traditional print newspapers are included into the analyses. Thus, further research should replicate this study with a broader media source context. On the other hand, If Sunstein is right in that internet breeds fragmentation and group polarization simply by motivating to consume only like-minded information and to avoid challenging views (2007), offline communication habits should also be compared with that of online platforms when investigation selectivity and polarization. Such a study could be able to reveal to what extent the mass Turkish public exercise partisan selective exposure and polarization. In addition, examining exposure to non-political news outlets and media sources would also give important insights on whether this polarization is limited to political sphere or not.

This thesis takes a picture of Turkish Twitter community regarding their media consumption behavior and its effect on polarization. However, it doesn't say anything about the differences between audience that are partisan/non-partisan and polarized/un-polarized. For example, what are the difference between partisan/polarized and moderate individuals in terms of their political message tones when communicating with each other? Does the partisan and cross-ideological selective exposure have an impact on that political communication tone? Further studies could focus on these differences and investigate whether being exposed to cross-cutting

political views have positive effect on political communication behaviors such as high levels of political tolerance, public deliberation, political empathy, civility and respect to alternative views and counter arguments. If so, developing strategies for motivating cross-ideological exposure and public deliberation instead of partisan selective exposure and enclaved deliberation would be a great advice for public authorities to reduce political polarization among Turkish society.

The variables of partisanship and partisan polarization depends upon the similar attitudes of Twitter users. Specifically, while the level of partisanship is created based on the number of pro-party deputies followed on Twitter, partisan polarization variable is created based on the absolute value of the difference between the partisanship score of the supported party and the average partisanship scores of the other parties. Considering that these two variables come from the same data set (following politicians) and that the polarization score is somehow determined by the partisanship score, the partisanship score used in this study might be an endogeneous variable on polarization. Therefore, the regression models used for predicting polarization with interactions between partisanship and selective news exposure might be biased and might not be representative of the association between partisan selective exposure and polarization.

Lastly, although the measurement strategies used in this study (i.e., following/unfollowing news outlets and politicians, retweeting like-minded accounts on Twitter, framing the own and oppositional parties) are related with the political attitudes, it might not still be clear whether the magnitude of these attitudes definitely refer to the attitude polarization. This suspicion mostly stems from the different definitions of the polarization. For example, Dimaggio et al. (1996) defines polarization as the

maximum divergence of opinions on a politically controversial issue as well as the process of increase in this divergence over time. This study neither measures Twitter users' opinions on political issues nor it investigates whether the distance between the issue positions diverge further over time. Therefore, the attitudes measured on Twitter might just be the expression of the political support and strong party-identification. Further studies should focus on issue positions and to what extent these positions stay polarized over time to investigate this phenomenon.

## REFERENCES

- Abramowitz, A. I., & Saunders, K. L. (1998). Ideological Realignment in the U.S. Electorate. *The Journal of Politics*, 60(3), 634–652. <https://doi.org/10.2307/2647642>
- Abramowitz, A. I., & Saunders, K. L. (2008). Is Polarization a Myth? *The Journal of Politics*, 70(2), 542–555. <https://doi.org/10.1017/S0022381608080493>
- Akyürek, D. S., & Koydemir, F. S. (2014). *Ethnic, Religious and Political Polarization in Turkey*. BILGESAM. Retrieved from <http://www.bilgesam.org/Images/Dokumanlar/0-262-2014070713kutup.pdf>
- Al Zamal, F, Liu, W., & Ruths, D. (2012). Homophily and latent attribute inference: Inferring latent attributes of twitter users from neighbors. Presented at the Proc. 6th International Conference on Weblogs and Social Media.
- An, J., Cha, M., Gummadi, K., & Crowcroft, J. (2011). Media Landscape in Twitter: A World of New Conventions and Political Diversity. Presented at the Fifth International AAAI Conference on Weblogs and Social Media.
- An, J., Cha, M., Gummadi, K., Crowcroft, J., & Quercia, D. (2012). Visualizing Media Bias through Twitter. *International AAAI Conference on Web and Social Media; Sixth International AAAI Conference on Weblogs and Social Media*. Retrieved from <https://www.aaai.org/ocs/index.php/ICWSM/ICWSM12/paper/view/4775>
- Andranik Tumasjan, Timm O. Sprenger, Philipp G. Sandner, & Isabell M. Welpe. (2010). Election Forecasts With Twitter: How 140 Characters

Reflect the Political Landscape. *Social Science Computer Review*, 29(4), 402–418. <https://doi.org/10.1177/0894439310386557>

Arceneaux, K., & Johnson, M. (2013). *Changing Minds or Changing Channels?: Partisan News in an Age of Choice*. University of Chicago Press.

Arceneaux, K., Johnson, M., & Murphy, C. (2012). Polarized Political Communication, Oppositional Media Hostility, and Selective Exposure. *The Journal of Politics*, 74(1), 174–186. <https://doi.org/10.1017/S002238161100123X>

Barberá, P. (2015). Birds of the Same Feather Tweet Together: Bayesian Ideal Point Estimation Using Twitter Data. *Political Analysis*, 23(1), 76–91. <https://doi.org/10.1093/pan/mpu011>

Batagelj, V., & Mrvar, A. (1998). Pajek—Program for Large Network Analysis. *Connections*, 21(2), 47–57.

Baum, M. A., & Groeling, T. (2008). New Media and the Polarization of American Political Discourse. *Political Communication*, 25(4), 345–365. <https://doi.org/10.1080/10584600802426965>

Bennett, W. L., & Iyengar, S. (2008). A New Era of Minimal Effects? The Changing Foundations of Political Communication. *Journal of Communication*, 58(4), 707–731. <https://doi.org/10.1111/j.1460-2466.2008.00410.x>

Berelson, B., Lazarsfeld, P. F., & McPhee, W. N. (1954). *Voting: A Study of Opinion Formation in a Presidential Campaign*. Chicago: University of Chicago Press.

Berry, J. M., & Sobieraj, S. (2014). *The outrage industry : political opinion media and the new incivility*. Oxford ; New York : Oxford University Press. Retrieved from <http://public.eblib.com/choice/publicfullrecord.aspx?p=1573138>

- Bilgiç, M. S., Koydemir, F. S., & Akyürek, S. (2014). Türkiye’de Kimlikler Arası Kutuplaşmanın Sosyal Mesafe Üzerinden Ölçümü ve Toplumsal Güvenliğe Etkisi. *Bilge Strateji*, 6(11). Retrieved from <http://dergipark.ulakbim.gov.tr/bs/article/view/5000153373>
- Bimber, B., & Davis, R. (2003). *Campaigning Online: The Internet in U.S. Elections*. Oxford University Press.
- Bishop, B. (2009). *The Big Sort: Why the Clustering of Like-Minded America is Tearing Us Apart* (1 edition). Boston: Mariner Books.
- Bland, J. M., & Altman, D. G. (2000). The odds ratio. *BMJ: British Medical Journal*, 320(7247), 1468–1468.
- Blondel, V. D., Guillaume, J.-L., Lambiotte, R., & Lefebvre, E. (2008). Fast unfolding of communities in large networks. *Journal of Statistical Mechanics: Theory and Experiment*, 44(10), P10008. <https://doi.org/10.1088/1742-5468/2008/10/P10008>
- Bode, L., & Dalrymple, K. E. (2014). Politics in 140 Characters or Less: Campaign Communication, Network Interaction, and Political Participation on Twitter. *Journal of Political Marketing*, 1–22. <https://doi.org/10.1080/15377857.2014.959686>
- Boutyline, A., & Willer, R. (2017). The Social Structure of Political Echo Chambers: Variation in Ideological Homophily in Online Networks. *Political Psychology*, 38(3), 551–569. <https://doi.org/10.1111/pops.12337>
- Brundidge, J. (2010). Encountering “Difference” in the Contemporary Public Sphere: The Contribution of the Internet to the Heterogeneity of Political Discussion Networks. *Journal of Communication*, 60(4), 680–700. <https://doi.org/10.1111/j.1460-2466.2010.01509.x>

- Calhoun, C. (1988). Populist Politics, Communications Media and Large Scale Societal Integration. *Sociological Theory*, 6(2), 219–241. <https://doi.org/10.2307/202117>
- Campbell, A., Converse, P. E., Miller, W. E., & Stokes, D. E. (1960). *The American Voter*. New York: John Wiley & Sons.
- Campbell, A., & Cooper, H. C. (1956). *Group Differences in Attitudes and Votes*. Ann Arbor, MI: Institute for Social Research, University of Michigan.
- Campbell, A., Gurin, G., & Miller, W. E. (1954). *The Voter Decides*. Evanston, IL: Row, Peterson.
- Campbell, A., & Kahn, R. L. (1952). *The People Elect a President*. Ann Arbor: Survey Research Center, Institute for Social Research, University of Michigan.
- Campbell, A., & Miller, W. E. (1957). The Motivational Basis of Straight and Split Ticket Voting. *American Political Science Review*, 51(2), 293–312.
- Çarkoglu, A., Baruh, L., & Yildirim, K. (2014). Press-Party Parallelism and Polarization of News Media during an Election Campaign: The Case of the 2011 Turkish Elections. *The International Journal of Press/Politics*, 19(3), 295–317. <https://doi.org/10.1177/1940161214528994>
- Chaffee, S. H., Saphir, M. N., Grap, J., Sandvig, C., & Hahn, K. S. (2001). Attention to Counter-Attitudinal Messages in a State Election Campaign. *Political Communication*, 18(3), 247–272. <https://doi.org/10.1080/10584600152400338>
- Dahlgren, P. (2005). The Internet, Public Spheres, and Political Communication: Dispersion and Deliberation. *Political Communication*, 22(2), 147–162. <https://doi.org/10.1080/10584600590933160>



- Davis, N. T., & Dunaway, J. L. (2016). Party Polarization, Media Choice, and Mass Partisan-Ideological Sorting. *Public Opinion Quarterly*, 80(S1), 272–297. <https://doi.org/10.1093/poq/nfw002>
- Dilliplane, S. (2014). Activation, Conversion, or Reinforcement? The Impact of Partisan News Exposure on Vote Choice. *American Journal of Political Science*, 58(1), 79–94.
- DiMaggio, P., Evans, J., & Bryson, B. (1996). Have American's Social Attitudes Become More Polarized? *American Journal of Sociology*, 102(3), 690–755. <https://doi.org/10.1086/230995>
- Druckman, J. N., & Bolsen, T. (2011). Framing, Motivated Reasoning, and Opinions About Emergent Technologies. *Journal of Communication*, 61(4), 659–688. <https://doi.org/10.1111/j.1460-2466.2011.01562.x>
- Druckman, J. N., Levendusky, M. S., & McLain, A. (2017). No Need to Watch: How the Effects of Partisan Media Can Spread via Interpersonal Discussions. *American Journal of Political Science*, n/a-n/a. <https://doi.org/10.1111/ajps.12325>
- Dunbar, R. I. M., Arnaboldi, V., Conti, M., & Passarella, A. (2015). The structure of online social networks mirrors those in the offline world. *Social Networks*, 43, 39–47. <https://doi.org/10.1016/j.socnet.2015.04.005>
- Dutta-Bergman, M. J. (2006). Community Participation and Internet Use after September 11: Complementarity in Channel Consumption. *Journal of Computer-Mediated Communication*, 11(2), 469–484. <https://doi.org/10.1111/j.1083-6101.2006.00022.x>
- Erişen, E. (2013). The Impact of Party Identification and Socially Supplied Disagreement on Electoral Choices in Turkey. *Turkish Studies*, 14(1), 53–73. <https://doi.org/10.1080/14683849.2013.766982>

- Eulau, H., & Siegel, J. W. (1981). Social Network Analysis and Political Behavior: A Feasibility Study. *The Western Political Quarterly*, 34(4), 499–509. <https://doi.org/10.2307/447464>
- Festinger, L. (1962). *A Theory of Cognitive Dissonance*. Stanford University Press.
- Fiorina, M. P., & Abrams, S. J. (2008). Political Polarization in the American Public. *Annual Review of Political Science*, 11(1), 563–588. <https://doi.org/10.1146/annurev.polisci.11.053106.153836>
- Fiorina, M. P., & Abrams, S. J. (2009). *Disconnect: The Breakdown of Representation in American Politics*. University of Oklahoma Press.
- Fiorina, M. P., Abrams, S. J., & Pope, J. (2005). *Culture war?: the myth of a polarized America*. Pearson Longman.
- Freedman, J. L. (1965). Preference for dissonant information. *Journal of Personality and Social Psychology*, 2(2), 287–289. <https://doi.org/10.1037/h0022415>
- Freedman, Jonathan L., D. O. S. (1966). Selective Exposure. In L. Berkowitz (Ed.), *Advances in Experimental Social Psychology* (pp. 58–98). New York: Academic Press. [https://doi.org/10.1016/S0065-2601\(08\)60103](https://doi.org/10.1016/S0065-2601(08)60103)
- Frey, D. (1986). Recent Research on Selective Exposure to Information. In L. Berkowitz (Ed.), *Advances in Experimental Social Psychology* (Vol. 19, pp. 41–80). Academic Press. [https://doi.org/10.1016/S0065-2601\(08\)60212-9](https://doi.org/10.1016/S0065-2601(08)60212-9)
- Garrett, R. K. (2006). Seeking Similarity, Not Avoiding Difference: Reframing the Ideological Selective Exposure Debate. Presented at the International Communication Association, Dresden International Congress Centre, Dresden, Germany. Retrieved from [http://citation.allacademic.com/meta/p\\_mla\\_apa\\_research\\_citation/](http://citation.allacademic.com/meta/p_mla_apa_research_citation/)

0/9/1/5/6/p91569\_index.html?phpsessid=pd5csp8v1h65s1ituis671fb54#citation

- Garrett, R. K. (2009a). Echo chambers online?: Politically motivated selective exposure among Internet news users<sup>1</sup>. *Journal of Computer-Mediated Communication*, 14(2), 265–285. <https://doi.org/10.1111/j.1083-6101.2009.01440.x>
- Garrett, R. K. (2009b). Politically Motivated Reinforcement Seeking: Reframing the Selective Exposure Debate. *Journal of Communication*, 59(4), 676–699. <https://doi.org/10.1111/j.1460-2466.2009.01452.x>
- Garrett, R. K., Carnahan, D., & Lynch, E. K. (2011). A Turn Toward Avoidance? Selective Exposure to Online Political Information, 2004–2008. *Political Behavior*, 35(1), 113–134. <https://doi.org/10.1007/s11109-011-9185-6>
- Garrett, R. K., Gvirsman, S. D., Johnson, B. K., Tsfati, Y., Neo, R., & Dal, A. (2014). Implications of Pro- and Counterattitudinal Information Exposure for Affective Polarization. *Human Communication Research*, 40(3), 309–332. <https://doi.org/10.1111/hcre.12028>
- Gentzkow, M., & Shapiro, J. M. (2011). Ideological Segregation Online and Offline. *The Quarterly Journal of Economics*, 126(4), 1799–1839. <https://doi.org/10.1093/qje/qjr044>
- Gentzkow, Matthew. (2016). *Polarization in 2016*. Stanford University: Toulouse Network for Information Technology Whitepaper. Retrieved from <https://web.stanford.edu/~gentzkow/research/PolarizationIn2016.pdf>
- Gerring, J. (2010). Causal Mechanisms: Yes, But.... *Comparative Political Studies*, 43(11), 1499–1526. <https://doi.org/10.1177/0010414010376911>

- Gezici Research Company. (2017). *2017 Referandum Survey*. Retrieved from [http://geziciarastirma.com/haber\\_detay/68/SON%20REFERANDUM%20ANKET%C4%B0/](http://geziciarastirma.com/haber_detay/68/SON%20REFERANDUM%20ANKET%C4%B0/)
- Green, D., Palmquist, P. B., & Schickler, P. E. (2004). *Partisan Hearts and Minds*. New Haven, Conn.; London: Yale University Press.
- Gvirsman, S. D. (2014). It's Not That We Don't Know, It's That We Don't Care: Explaining Why Selective Exposure Polarizes Attitudes. *Mass Communication and Society*, 17(1), 74–97. <https://doi.org/10.1080/15205436.2013.816738>
- Habermas, J. (1989). *The structural transformation of the public sphere: An Inquiry into a category of Bourgeois Society*. (T. Burger, Trans.) (Vol. null). Massachusetts Institute of Technology Press.
- Halberstam, Y., & Knight, B. (2016). Homophily, group size, and the diffusion of political information in social networks: Evidence from Twitter. *Journal of Public Economics*, 143, 73–88. <https://doi.org/10.1016/j.jpubeco.2016.08.011>
- Hallin, D. C., & Mancini, P. (2004). *Comparing Media Systems: Three Models of Media and Politics*. Cambridge: Cambridge University Press.
- Hargittai, Eszter, Gallo, Jason, & Zehnder, Sean. (2005). Mapping the Political Blogosphere: An Analysis of Large-Scale Online Political Discussions. Presented at the International Communication Association, New York. Retrieved from [http://www.allacademic.com/meta/p15026\\_index.html](http://www.allacademic.com/meta/p15026_index.html)
- Hetherington, M. J. (2001). Resurgent Mass Partisanship: The Role of Elite Polarization. *American Political Science Review*, 95(3), 619–631. <https://doi.org/10.1017/S0003055401003045>
- Himmelboim, I., McCreery, S., & Smith, M. (2013). Birds of a Feather Tweet Together: Integrating Network and Content Analyses to Examine

Cross-Ideology Exposure on Twitter. *Journal of Computer-Mediated Communication*, 18(2), 40–60. <https://doi.org/10.1111/jcc4.12001>

Horwitz, S. N., & Nir, L. (2015). How politics-news parallelism invigorates partisanship strength. *International Political Science Review*, 36(2), 153–167. <https://doi.org/10.1177/0192512113516900>

Howison, J., Wiggins, A., & Crowston, K. (2011). Validity Issues in the Use of Social Network Analysis with Digital Trace Data. *Journal of the Association for Information Systems*, 12(12). Retrieved from <http://aisel.aisnet.org/jais/vol12/iss12/2>

Huckfeldt, R., Mendez, J. M., & Osborn, T. (2004). Disagreement, Ambivalence, and Engagement: The Political Consequences of Heterogeneous Networks. *Political Psychology*, 25(1), 65–95.

Huckfeldt, R. R., & Sprague, J. (1995). *Citizens, Politics and Social Communication: Information and Influence in an Election Campaign*. Cambridge University Press.

Institutional Social Responsibility Organisation. (2016). *Dimensions of Political Polarization in Turkey*. Retrieved from <http://www.internethaber.com/turkiyede-kutuplasma-anketi-sonuclari-yanitlar-soke-etti-foto-galerisi-1562619.htm>

Iyengar, S., & Hahn, K. S. (2009). Red Media, Blue Media: Evidence of Ideological Selectivity in Media Use. *Journal of Communication*, 59(1), 19–39. <https://doi.org/10.1111/j.1460-2466.2008.01402.x>

Iyengar, S., Sood, G., & Lelkes, Y. (2012). Affect, Not Ideology: A Social Identity Perspective on Polarization. *Public Opinion Quarterly*, 76(3), 405–431. <https://doi.org/10.1093/poq/nfs038>

Jacobson, G. C. (2003). Partisan Polarization in Presidential Support: The Electoral Connection. *Congress & the Presidency*, 30(1), 1–36. <https://doi.org/10.1080/07343460309507855>

John Horrigan, Kelly Garrett, & Paul Resnick. (2004). *The Internet and democratic debate*. Retrieved from [http://www.pewinternet.org/files/old-media/Files/Reports/2004/PIP\\_Political\\_Info\\_Report.pdf.pdf](http://www.pewinternet.org/files/old-media/Files/Reports/2004/PIP_Political_Info_Report.pdf.pdf)

Johnson, T. J., Bichard, S. L., & Zhang, W. (2009). Communication Communities or “CyberGhettos?”: A Path Analysis Model Examining Factors that Explain Selective Exposure to Blogs1. *Journal of Computer-Mediated Communication*, 15(1), 60–82. <https://doi.org/10.1111/j.1083-6101.2009.01492.x>

Jungherr, A. (2019). How Big Data Informs Political Communication. In N. J. Stroud & S. McGrego (Eds.), *Digital Discussions*. New York: NY: Routledge . (Forthcoming).

Jungherr, A., Schoen, H., Posegga, O., & Jürgens, P. (2016). Digital Trace Data in the Study of Public Opinion: An Indicator of Attention Toward Politics Rather Than Political Support. *Social Science Computer Review*, 35(3), 336–356. <https://doi.org/10.1177/0894439316631043>

Katz, E., & Lazarsfeld, P. F. (1955). *Personal influence: The part played by people in the flow of mass communications*. New York: The Free Press.

Key, V. O. J., & Munger, F. (1959). Social Determinism and Electoral Decision: The Case of Indiana. In B. Eugene & A. J. Brodbeck (Eds.), *American voting behavior*. Glencoe: The Free Press.

Kiriş, H. M. (2010). Polarized Turkey. *Toplum ve Demokrasi*, 4((8-9-10)), 203–204.

Kiriş, H. M. (2012). The CHP: From the Single Party to the Permanent Main Opposition Party. *Turkish Studies*, 13(3), 397–413. <https://doi.org/10.1080/14683849.2012.717445>

- Klapper, J. T. (1960). *Effects of Mass Communication* (1st edition). Glencoe (Illinois): Free Press.
- Knobloch-Westerwick, S. (2012). Selective Exposure and Reinforcement of Attitudes and Partisanship Before a Presidential Election. *Journal of Communication*, 62(4), 628–642. <https://doi.org/10.1111/j.1460-2466.2012.01651.x>
- Knobloch-Westerwick, S., & Jingbo Meng. (2009). Looking the Other Way: Selective Exposure to Attitude-Consistent and Counterattitudinal Political Information. *Communication Research*, 36(3), 426–448. <https://doi.org/10.1177/0093650209333030>
- Knoke, D. (1990). *Political Networks, The Structural Perspective*. New York: Cambridge University Press.
- Lavine, H., Borgida, E., & Sullivan, J. L. (2000). On the Relationship Between Attitude Involvement and Attitude Accessibility: Toward a Cognitive-Motivational Model of Political Information Processing. *Political Psychology*, 21(1), 81–106. <https://doi.org/10.1111/0162-895X.00178>
- Lazarsfeld, P. F., Berelson, B., & Gaudet, H. (1944). *The People's Choice: How the Voter Makes Up His Mind in a Presidential Campaign*. New York: Columbia University Press.
- Lelkes, Y. (2016). Mass Polarization: Manifestations and Measurements. *Public Opinion Quarterly*, 80(S1), 392–410. <https://doi.org/10.1093/poq/nfw005>
- Lelkes, Y., Sood, G., & Iyengar, S. (2017). The Hostile Audience: The Effect of Access to Broadband Internet on Partisan Affect. *American Journal of Political Science*, 61(1), 5–20. <https://doi.org/10.1111/ajps.12237>
- Leon Festinger. (1954). A Theory of Social Comparison Processes. *Human Relations*, 7(2), 117–140. <https://doi.org/10.1177/001872675400700202>

- Levendusky, M. (2009). *The Partisan Sort: How Liberals Became Democrats and Conservatives Became Republicans* (1 edition). Chicago: University of Chicago Press.
- Levendusky, M. (2013). *How Partisan Media Polarize America* (1 edition). University of Chicago Press.
- Levendusky, M. (2014). Changing Minds or Changing Channels? Partisan News in an Age of Choice. By Arceneaux Kevin and Johnson Martin . Chicago: University of Chicago Press, 2013. 244p. *Perspectives on Politics*, 12(2), 474–475. <https://doi.org/10.1017/S1537592714001030>
- Levendusky, M. (2017). *Partisan Media and Polarization: Challenges for Future Work*. Interactive Factory. Retrieved from <http://politics.oxfordre.com/view/10.1093/acrefore/9780190228637.001.0001/acrefore-9780190228637-e-50>
- Lin, C. A. (2009). Selective News Exposure, Personal Values, and Support for the Iraq War. *Communication Quarterly*, 57(1), 18–34. <https://doi.org/10.1080/01463370802662440>
- Lowin, A. (1967). Approach and avoidance: Alternate modes of selective exposure to information. *Journal of Personality and Social Psychology*, 6(1), 1–9. <https://doi.org/10.1037/h0024531>
- Marcus, G. E., Neuman, W. R., & MacKuen, M. (2000). *Affective Intelligence and Political Judgment*. University of Chicago Press.
- Mayer-Schönberger, V., & Cukier, K. (2014). *Big Data: A Revolution That Will Transform How We Live, Work, and Think* (Reprint edition). Boston: Eamon Dolan/Mariner Books.
- McCarty, N., Poole, K. T., & Rosenthal, H. (2016). *Polarized America: The Dance of Ideology and Unequal Riches*. MIT Press.



- McKenna, K. Y. A., & Bargh, J. A. (2000). Plan 9 From Cyberspace: The Implications of the Internet for Personality and Social Psychology. *Personality and Social Psychology Review*, 4(1), 57–75. [https://doi.org/10.1207/s15327957pspr0401\\_6](https://doi.org/10.1207/s15327957pspr0401_6)
- Meffert, M. F., Chung, S., Joiner, A. J., Waks, L., & Garst, J. (2006). The Effects of Negativity and Motivated Information Processing During a Political Campaign. *Journal of Communication*, 56(1), 27–51. <https://doi.org/10.1111/j.1460-2466.2006.00003.x>
- Mill, J. S. (1859). *On Liberty*. London: Longman, Roberts, & Green Co.
- Morales, A. J., Borondo, J., Losada, J. C., & Benito, R. M. (2015). Measuring political polarization: Twitter shows the two sides of Venezuela. *Chaos*, 25(3), 033114. <https://doi.org/10.1063/1.4913758>
- Mullainathan, S., & Shleifer, A. (2005). The Market for News. *American Economic Review*, 95(1), 1031–1053.
- Mutz, Diana C. (2002). Cross-Cutting Social Networks: Testing Democratic Theory in Practice. *The American Political Science Review*, 96(1), 111–126.
- Mutz, Diana C. (2006). *Hearing the Other Side: Deliberative versus Participatory Democracy* (1 edition). Cambridge ; New York: Cambridge University Press.
- Mutz, Diana C., & Martin, P. S. (2001). Facilitating Communication Across Lines of Political Difference: The Role of Mass Media. *American Political Science Review*, 95(1), 97–114.
- Newman, N., Fletcher, R., Kalogeropoulos, A., Levy, D., & Nielsen, R. K. (2017). *Reuters Institute Digital News Report 2017* (p. 136). Retrieved from

[https://reutersinstitute.politics.ox.ac.uk/sites/default/files/Digital%20News%20Report%202017%20web\\_0.pdf](https://reutersinstitute.politics.ox.ac.uk/sites/default/files/Digital%20News%20Report%202017%20web_0.pdf)

Newman, N., Fletcher, R., Levy, D., & Nielsen, R. K. (2016). *Reuter Institute Digital News Report 2016*. Retrieved from [http://reutersinstitute.politics.ox.ac.uk/sites/default/files/research/files/Digital%2520News%2520Report%25202016.pdf?utm\\_medium=referral&utm\\_source=digitalnewsreport.org](http://reutersinstitute.politics.ox.ac.uk/sites/default/files/research/files/Digital%2520News%2520Report%25202016.pdf?utm_medium=referral&utm_source=digitalnewsreport.org)

Papacharissi, Z. (2002). The virtual sphere: The internet as a public sphere. *New Media & Society*, 4(1), 9–27. <https://doi.org/10.1177/14614440222226244>

Pariser, E. (2011). *The Filter Bubble: What The Internet Is Hiding From You*. Penguin UK.

Perryman, M. R. (2017). *Public Perceptions of Partisan Selective Exposure* (Ph.D.). Ann Arbor, United States. Retrieved from <https://search.proquest.com/docview/1949768662/abstract/EA3741E597BE4B72PQ/9>

Petty, R. E., & Krosnick, J. A. (2014). *Attitude strength: Antecedents and consequences*. Psychology Press.

Pew Research Center. (2014). *Political Polarization in the American Public*. Retrieved from <http://www.people-press.org/2014/06/12/appendix-a-the-ideological-consistency-scale/>

Prior, M. (2007). *Post-broadcast democracy: How media choice increases inequality in political involvement and polarizes elections*. (null, Ed.) (Vol. null).

Prior, Markus. (2007). *Post-Broadcast Democracy: How Media Choice Increases Inequality in Political Involvement and Polarizes Elections* (1 edition). New York: Cambridge University Press.

- Prior, Markus. (2013). Media and Political Polarization. *Annual Review of Political Science*, 16(1), 101–127. <https://doi.org/10.1146/annurev-polisci-100711-135242>
- Rainie, L., & Wellman, B. (2014). *Networked: The New Social Operating System* (Reprint edition). The MIT Press.
- Sayarı, S. (2007). Towards a New Turkish Party System? *Turkish Studies*, 8(2), 197–210.
- Slater, M. D. (2007). Reinforcing Spirals: The Mutual Influence of Media Selectivity and Media Effects and Their Impact on Individual Behavior and Social Identity. *Communication Theory*, 17(3), 281–303. <https://doi.org/10.1111/j.1468-2885.2007.00296.x>
- Smith, A., & Rainie, L. (2010). *8% of online Americans use Twitter*. Pew Internet & American Life Project. <https://doi.org/10.7228/manchester/9780719074462.003.0001>
- Smith, S. M., Fabrigar, L. R., & Norris, M. E. (2008). Reflecting on Six Decades of Selective Exposure Research: Progress, Challenges, and Opportunities. *Social and Personality Psychology Compass*, 2(1), 464–493. <https://doi.org/10.1111/j.1751-9004.2007.00060.x>
- Chaffee, S. H., & Miyo, Y. (1983). Selective Exposure and the reinforcement hypothesis: An Intergenerational Panel Study of the 1980 Presidential Campaign. *Communication Research*, 10(1), 3–36. <https://doi.org/10.1177/009365083010001001>
- Stromer-Galley, J. (2003). Diversity of Political Conversation on the Internet: Users' Perspectives. *Journal of Computer-Mediated Communication*, 8(3), 0–0. <https://doi.org/10.1111/j.1083-6101.2003.tb00215.x>
- Stroud, N. J. (2006). *Selective exposure to partisan information* (Ph.D.). Ann Arbor, United States. Retrieved from

<https://search.proquest.com/docview/305258821/abstract/8EB74A32BD9C4C7DPQ/1>

Stroud, N. J. (2008). Media Use and Political Predispositions: Revisiting the Concept of Selective Exposure. *Political Behavior*, 30(3), 341–366. <https://doi.org/10.1007/s11109-007-9050-9>

Stroud, N. J. (2010). Polarization and Partisan Selective Exposure. *Journal of Communication*, 60(3), 556–576. <https://doi.org/10.1111/j.1460-2466.2010.01497.x>

Sunstein, C. R. (2002). The Law of Group Polarization. *Journal of Political Philosophy*, 10(2), 175–195. <https://doi.org/10.1111/1467-9760.00148>

Sunstein, C. R. (2007). *Republic.com 2.0*. Princeton University Press. Retrieved from <http://www.jstor.org/stable/j.ctt7tbsw>

Sunstein, C. R. (2011). *Going to Extremes: How Like Minds Unite and Divide* (Reprint edition). New York: Oxford University Press.

Taber, C. S., & Lodge, M. (2006). Motivated Skepticism in the Evaluation of Political Beliefs. *American Journal of Political Science*, 50(3), 755–769. <https://doi.org/10.1111/j.1540-5907.2006.00214.x>

Thornal, K. (2015). *Partisan media and polarized politics: A meta-analysis of the relationship between partisan selective exposure and political polarization* (M.A.). Ann Arbor, United States. Retrieved from <https://search.proquest.com/docview/1698104091/abstract/3C679A8F082648D4PQ/4>

Trilling, D., van Klingeren, M., & Tsfati, Y. (2017). Selective Exposure, Political Polarization, and Possible Mediators: Evidence From the Netherlands. *International Journal of Public Opinion Research*, 29(2), 189–213. <https://doi.org/10.1093/ijpor/edw003>

- Tsfati, Y., & Chotiner, A. (2016). Testing the Selective Exposure–Polarization Hypothesis in Israel Using Three Indicators of Ideological News Exposure and Testing for Mediating Mechanisms. *International Journal of Public Opinion Research*, 28(1), 1–24. <https://doi.org/10.1093/ijpor/edv001>
- Wojcieszak, M. (2009). “Carrying Online Participation Offline” — Mobilization by Radical Online Groups and Politically Dissimilar Offline Ties. *Journal of Communication*, 59(3), 564–586. <https://doi.org/10.1111/j.1460-2466.2009.01436.x>
- Yang, J., Rojas, H., Wojcieszak, M., Aalberg, T., Coen, S., Curran, J., ... Tiffen, R. (2016). Why Are “Others” So Polarized? Perceived Political Polarization and Media Use in 10 Countries. *Journal of Computer-Mediated Communication*, 21(5), 349–367. <https://doi.org/10.1111/jcc4.12166>
- Yonghwan Kim. (2015). Does Disagreement Mitigate Polarization? How Selective Exposure and Disagreement Affect Political Polarization. *Journalism & Mass Communication Quarterly*, 92(4), 915–937. <https://doi.org/10.1177/1077699015596328>
- YouGov. (2008). *Anglo-Saxon Attitudes: A Survey of British and American Views of the World*. Retrieved from <http://www.economist.com/media/pdf/FullPollData.pdf>

## APPENDICES

### A. WHOLE LIST OF TWITTER ACCOUNTS THAT ARE RETWEETED BY THE SAMPLE TWITTER AUDIENCE<sup>12</sup>.

#### Pro-government accounts (n=194):

@RT\_Erdogan(9848), @anadolujansi(8618), @06melihgokcek(8199),  
@yenisafak(7039), @dbdevletbahceli(7010), @tcbestepe(6740), @fatihtezcan(6146),  
@tvahaber(5854), @samiltayyar27(5705), @trthaber(5581), @stargazete(5454),  
@GkhnKhrman(5121), @TC\_Basbakan(5041), @SavciSayan(4997), @Sabah(4679),  
@suleymansoylu(4536), @themarginale(4448), @ikalin1(4242),  
@teroretavizyok\_(4099), @Haber7(3991), @BurhanKuzu(3960),  
@UstAkilOyunlari(3920), @yirmidorttv(3836), @ensonhaber(3600),  
@Ahmet\_Davutoglu(3573), @slmhktn(3569), @memetsimsek(3508),  
@MevlutCavusoglu(3479), @yenisafakwriter(3477), @mkulunk(3458),  
@ademozkose(3287), @turgayguler(3277), @Akpatri(3267), @omerturantv(3223),  
@mustafarmagan(3134), @ugur\_isilak(3130), @MHP\_Bilgi(3106),  
@hasandogan(3070), @Aksam(2965), @GizliArsivTR(2944), @Malikejder47(2928),  
@hilal\_kaplan(2912), @PkkyA\_Afyok(2839), @ihhinsaniyardim(2827),  
@hikmetgenc(2808), @drbetulsayan(2797), @EgemenBagis(2788), @varank(2753),  
@doganburak29(2751), @NumanKurtulmus(2742), @kendinelai(2725),  
@aDilipak(2680), @HarunAlanoglu(2629), @dalierzincanli(2619),  
@TheLaikYobaz(2509), @melihaltinok(2477), @sevdaturkusev(2446),  
@VeyselEroglu(2446), @bybekirbozdag(2408), @KadirMisiroglu(2384),  
@yeniakit(2260), @cemkucuk55(2242), @slymnoz(2222), @TurkmanDagi(2220),  
@FatmaSahin(2167), @kilicarslan\_is(2156), @ersoydede(2147),  
@ibrahimkaragul(2146), @BilginBirand(2137), @zhl\_cskn(2104),  
@Mehmet\_Ali\_ONEL(2080), @aziz\_ustell(2058), @turanbulent(2056),  
@EremSenturk(2053), @yigitbulutt(2038), @kenan\_kiran(2032),  
@markaresayan(2030), @ackilic76(2020), @suatkilic(2001), @medyaadami(1991),  
@BA\_Yildirim(1978), @haciykk(1954), @bekiservet(1935), @tvnet(1892),  
@turkiyegazetesi(1890), @tgrthabertv(1888), @sarseven(1870),  
@BeratAlbayrak(1797), @kelkitlioglumrt(1795), @ensari622(1770),  
@mecertas(1766), @sevdamrabbim(1750), @TeBuK34(1744), @omerrcelik(1727),  
@HalilOzturk60(1704), @cemilebayraktr(1697), @fikriisik(1696),

---

<sup>12</sup> The numbers in parentheses represent how many different users in the sample retweeted an account.

@TwitBakani(1672), @bayramzilan(1643), @huseyingulercee(1634),  
@osmanlicinari(1619), @HasmetBABA(1616), @AyYildizz17(1613),  
@EmineDemir\_(1603), @AKGencilikGM(1598), @Swetnvmbr(1597),  
@oktayvural(1597), @kendimce\_ben(1582), @AKGaziantep27(1561),  
@ikbl0571(1541), @ardanzenturk(1536), @emirbereket(1526),  
@enginyaman1979(1518), @mustafaatas(1512), @internethaber(1504),  
@farukonalan(1497), @filiz175(1483), @EnginArdc\_(1482), @uguronal(1468),  
@AK\_suHandan(1467), @maske3g(1463), @EmreErcis1(1463), @SiyasiHafiza(1439),  
@Sevkiyilmaz(1439), @06Kartalz(1434), @saitcamlica(1430), @gizliarsiv(1429),  
@abdulhamitgul(1423), @OzelHarekaTR(1417), @secondvirus(1406),  
@bavehayran(1405), @Slck\_byrktr(1405), @saidercan(1387), @FUATUGUR(1383),  
@MehToprak(1378), @ihacomtr(1372), @abdestalanlaik(1369), @derinanaliz(1367),  
@Y\_Akdogan(1357), @MuratAIan(1333), @orhankrkrt(1330),  
@A\_Boynukalin(1330), @senaidemirci(1327), @hiyibildiren(1326),  
@johkuvvetler(1319), @Gazete\_Yenicag(1314), @mahirunal(1314),  
@\_cevdetyilmaz(1312), @RTECanli(1310), @omerdongeloglu(1309),  
@cumaiçten(1303), @BakBunuYazdim(1296), @ergn\_diler(1287), @fuat2023(1284),  
@FreeTurkmens(1281), @zihnicakir(1280), @NuhAlbayrak(1279),  
@Mihriban\_merent(1278), @farukcelikcomtr(1276), @AhmetKursatK(1275),  
@OlcayKilavuz(1255), @oznurcalik(1253), @06hasanbulbul(1247),  
@saffetsancakli(1246), @emrullahisler(1245), @misvakdergi(1239),  
@Baris\_DR(1233), @TRSpecialForces(1224), @Sarikli\_Voyvoda(1215),  
@Y\_Bahadiroglu(1207), @olcokcevat(1203), @ibrahimkalin\_(1200),  
@UmmetciSiyaset(1199), @ibrahimtenekeci(1197), @OA\_Bak(1192),  
@ulkucumedyacom(1182), @detroitlikizil(1181), @ulketv(1176),  
@SelimTemurci(1172), @Galip\_Ozturk(1160), @Selimcerrah(1149),  
@muhtesem40(1140), @esma\_fb\_3437(1140), @takvim(1132),  
@DobraUzunAdam(1108), @SosyalBedevi27(1098), @myildizdogann(1086),  
@banuel(1084), @idriskardas(1082), @hucurat\_10(1078), @ZeybekciNihat(1069),  
@Ak\_Tweest(1053), @orhannatak(1048), @ufukcoskunn(1047),

### **Oppositional Accounts (n=329):**

@cumhuriyetgzt(10893), @gazetesozcu(8783), @kacsaatoldunet(8652),  
@BirGun\_Gazetesi(8524), @t24comtr(8118), @candundaradasi(7949),  
@erenerdemnet(7926), @ismailsaymaz(7473), @odatv(7346), @fatihportakal(7244),  
@DikenComTr(7101), @barisatay(6884), @vekilince(6806), @ATuncayOzkan(6743),  
@kilicdaroglu(6270), @AtillaTasNet(6202), @aykuterdogdu(6149),  
@solhaberportali(6082), @ozgurumcu(5795), @nedimsener2010(5789),  
@ugurdundarsozcu(5593), @haykobagdat(5190), @orhanaydin6(5148),  
@acikcenk(5128), @DrSinanOgan(5019), @ihsaneliacik(4954),  
@meral\_aksener(4935), @metinfeyzioglu(4906), @mustafahos(4722),  
@haluk\_levent(4700), @bulentmumay(4633), @KucukkayaIsmail(4543),

@evrenselgzt(4517), @ProfDemirtas(4513), @LutfuTurkkan(4512),  
@barisyarkadas(4442), @enveraysevera(4425), @YilmazKalem\_(4333),  
@SedefKabas(4216), @mustafabalbay(4202), @MSTanrikulu(4185),  
@umitozdog(4162), @koraycaliskan(4154), @sahmetsahmet(4100),  
@\_Hayalet\_\_(3934), @Mustafaselanik3(3873), @SMEYDAN(3836),  
@FidelOKAN(3834), @hocanizcomtr(3814), @YrGngelopoulos(3724),  
@JeansBiri(3705), @fatih\_yasli(3658), @lvntozrn(3608), @dokuz8haber(3596),  
@eczozgurozel(3571), @DrSteveneu(3503), @azyazarozyazarr(3490),  
@herkesicinCHP(3489), @husnumahalli(3470), @MTanal(3467),  
@SunaVarol\_(3462), @ZaferArapkirli(3424), @SozcuArsiv(3424),  
@avneo\_ottoman(3324), @eacarar(3323), @tokcem(3321), @emrkongar(3316),  
@RustemBatum(3213), @EmreUslu(3212), @senerabdullatif(3197),  
@abcgazete(3197), @tgmcelebi(3178), @DarbukatorBarym(3105), @DahiBilal(3034),  
@ETemelkuran(3022), @Halitisci(2974), @ttbamteli(2933), @turyildizbicer(2903),  
@halktvcomtr(2882), @HuseyinAygün62(2876), @HDPgenelmerkezi(2845),  
@uzobey(2808), @imamefendi\_(2799), @ilerihaber(2771), @avcimucahit(2762),  
@efkanbolac(2749), @KeremALTIPARMAK(2705), @errdemglr(2704),  
@KomunistBaskann(2677), @caapulcukiz(2665), @fehmtastekin(2656),  
@hdpdemirtas(2607), @elifilgaz(2606), @KarsiGazete(2605),  
@mywayTurkey(2595), @m\_cemilkilic(2584), @veliagbaba(2573), @tr724com(2523),  
@hakansukur(2512), @mansuryavas06(2504), @HergelePostasi(2503),  
@aylin\_kotil(2501), @meldaonur(2501), @Haberdar(2494),  
@AvGurkanKorkmaz(2493), @otekilerpostasi(2488), @selinsayekboke(2486),  
@super\_titiz(2482), @EvitanNeslihan(2441), @velisacilik(2435), @muhalif\_c(2396),  
@MBekaroglu(2389), @WashingtonPoint(2383), @MehmetAltanFan(2381),  
@yilmazsozcu(2366), @\_TersAdam(2347), @ttractatus(2344),  
@cemalokanyuksel(2333), @aliturksen(2332), @bianet\_org(2326),  
@kolektifler(2318), @AydinlikGazete(2309), @mkirikkanat(2307),  
@hayriituncc(2303), @banuguven(2295), @Qestuka(2284), @asliaydintasbas(2277),  
@harunkaranfilci(2266), @zeynabelle(2221), @can\_atakli\_(2205), @adalet\_tv(2186),  
@BilseniziyiOlur(2157), @nihatsirdar(2153), @ErtugrulGunay(2126),  
@ertgrlalbyrk(2125), @imc\_televizyonu(2118), @AylinNazliaka(2116),  
@politikbaykus(2116), @serakadigil(2104), @ferhattunc(2103),  
@KadriGursel(2099), @ayhanbilgen(2078), @KacSaatOldu1(2061),  
@BaturayCevik(2051), @cosknbejr2(2050), @hsncml(2047), @senerabdullati(2040),  
@kuzeyormanlari(2022), @cancananvatan(2012), @ismaildukel(2008),  
@aliarslan3460(2007), @TayyipAga(2006), @EAksunger(2006),  
@gercekgundem(1996), @ilkerkarli(1994), @Hilalzcan20(1990), @perapea(1989),  
@ahhakverdi(1981), @ceydak(1970), @alicanuludag(1968), @bunsenbeki(1965),  
@Yazar212(1962), @yurtgazetesi(1948), @ilbering(1942), @UmutOranCHP(1937),  
@NuriyeGulmen(1912), @nasuhbektas(1897), @Baysal048(1896),  
@zek\_i\_nesli(1876), @daim\_munzevi(1876), @SonVesayet(1869), @dzepm(1866),



@cicekabbasbilo(1864), @ayagakalktaksim(1860), @gurseltekin34(1834),  
@Ozguruz\_org(1832), @halukpeksen(1831), @draliseker(1822), @ebabahan(1813),  
@OduncuTimi(1805), @gazeteduvar(1801), @HurAyse(1791), @ayhangureltc(1766),  
@AgirelMurat(1755), @ommerhayyam(1744), @irfanaktans(1729),  
@MaliGuller(1723), @ilhanchihaner(1716), @cigdemtoker(1715), @CekirgeTV(1710),  
@SemihOzakca(1703), @Umit\_Kocasakal(1691), @aozturk70(1688),  
@fatmacumhurefe(1678), @baristerkoglu(1676), @gokhanozbek(1675),  
@Orsatramola(1671), @OzgurrGudem(1667), @hsoneryalcin(1655),  
@Halkevleri(1652), @BerilDeniz77(1651), @ATAKIIZI(1648),  
@drgurbuzcapan1(1635), @korayaydintr(1631), @AytunCiray(1628),  
@avmurate(1626), @caglarcilara(1623), @mhulkicevizoglu(1615),  
@BirlesikHaziran(1611), @aktif\_haber(1593), @oencueonur(1589),  
@meraldanis(1582), @AksiAdam\_(1559), @zatungcom(1558), @Aslnmhmt(1555),  
@arzuylzz(1554), @sefa\_said(1536), @SSSBBL777(1528), @bilgingokberk(1518),  
@ameddicleT(1508), @RifatDogann(1504), @TupcuFiko\_\_(1498),  
@GokhanVots(1496), @gergerliogluof(1487), @turandursun06(1482),  
@RuhatMengi34(1478), @hvmoltke(1475), @yusufhalacoglu(1474),  
@Srcn\_Syn(1463), @barispehlivan(1453), @dolumetrobus(1447), @fasibel(1442),  
@denizvemarti1(1439), @merdanyanardag(1439), @ceyhunirgil(1425),  
@av\_ugurpoyraz(1424), @direnvekazan(1418), @hzlandrc(1416), @AtaUlak(1410),  
@varcharian(1409), @Karacabey75(1409), @GaroPaylan(1406),  
@davuIcuvedat(1406), @TarikToros(1398), @sedatlaciner(1398),  
@Fehim\_Isik(1396), @SLuleci(1393), @HsnBozkurt(1382), @OyveOtesi(1381),  
@umit\_k(1380), @SensinYasak(1374), @faikoztrak(1370), @alper\_tas(1368),  
@izmirgibi(1357), @Turkeydeiskence(1347), @ozge\_mumcu(1347), @tturenc(1338),  
@safakpavey(1336), @Raz\_iye(1327), @ceLALce(1325), @ugurses(1319),  
@nasuhmahruki(1308), @tuncer\_es(1298), @direncigdem(1288), @celalulgen(1288),  
@bskazizkocaoglu(1288), @Murat\_ide(1286), @ezgibasaran(1282),  
@Atikopruluoglu(1280), @Cavbella84(1276), @Altiok1919(1274),  
@Bahceshr\_Golet(1269), @GaziCaglar(1260), @tezelali(1258), @mustfsnmz(1250),  
@\_ElifYilmaz\_(1247), @burcuas(1239), @denizyildirim79(1238),  
@hhakkikahveci(1235), @AteUrora(1234), @baysal\_nurcan(1228), @ASalepci(1223),  
@Odak2014(1223), @UfukUras(1222), @edipyuksel(1217), @alimuratirat(1217),  
@cmhr1907(1217), @ArsivUnutmaz(1215), @Akif\_Hamzacebi(1213),  
@sadem\_che(1211), @mkaomercetur(1209), @zerqddt(1207),  
@AysenurArslan50(1206), @kacsaatoldu\_tc(1206), @leylaalp(1204),  
@levent\_kazak(1199), @siyasifenomen(1197), @ORHANBURSALI(1197),  
@serkanaltunigne(1196), @tahsintarhan(1193), @TC\_SERDARR(1183),  
@fguzfguz(1182), @Luckyladybird15(1180), @gunesduru(1180), @yvzah(1177),  
@umitalan(1174), @liberaLDP(1173), @M\_Sarigul(1169), @ilkay\_\_y(1168),  
@vdemirbey(1165), @zaytungbey(1153), @MahirCaglayanTR(1151),  
@gezgin55(1147), @MarksistLeninst(1143), @tolgademir96(1143),

@redkitkovboy80(1140), @ilhantasci(1137), @WHeisinberg(1136),  
@SUAVI\_SUAVI(1136), @hilmihacaloglu(1136), @Alidogalli(1135),  
@Nesrinnas(1133), @cngzkync(1111), @PinarAYDINLAR(1107), @fpolat69(1079),  
@kemalgoktas(1071), @ahuturker34(1057), @iremafsin(1054),  
@SaltukBugraTurk(1049).

## B. LIST OF POLITICAL KEYWORDS USED TO CREATE "POLITICAL INTEREST" VARIABLE

15 Temmuz, 17-25 Aralık, 28 Şubat, ABD, Abdullah Gül, adalet, adil öksüz, Afrin/Efrin, ağababa, Ahmet Altan, ahmet şık, ak parti, AKP, aleviler, algı operasyon, Ali İsmail Korkmaz, Alman, ambargo, amed dicle, Amerika, anarşi, anayasa, arakan, araştırma komisyonu, Atatürk, ateist, ateizm, ateşkes, Avrupa, ayakkabı kutusu, ayasofya, bağımsızlık, bakan, balyoz, Baransu, Barzani, başbakan, Başbuğ, Başkanlık, başörtü, batı medeniyeti, Baykal Kaseti, BBP, Berkin elvan, beyaz türkler, Preet Bhrara, Bilal Erdoğan, Birleşmiş Milletler, bombacı, bombalı saldırı, BOP eş başkanı, bölücü, bürokrasi, bürokrat, büyük birlik partisi, büyükelçi, Bylock, Can Dündar, casus, Cehape, Cem Küçük, cemaat, cemevi, CHP, CIA, Cizre, cumhurbaşkanı, Cumhuriyet, çözüm süreci, daeş/deaş, darbe, dava adamı, Davutoğlu, demokrasi, demokratik, deniz yücel, devlet, Devlet Bahçeli, devletin bekası, devrim, DHKP, dış güçler, Dışişleri, diktatör, dindar, diplomat, direniş, dokunulmazlık, dünya lideri, düşman, El Nusra, elçilik, emekçi, emperyalizm, Emre Uslu, Enes Berberoğlu, enis berberoğlu, ensar, Erbakan, ergenekon, ermeni, Esad, eş başkan, eşitlik, faiz lobisi, faşist, Fethullah, FETÖ, Filistin, Fuat avni, Gazze, gençlik kolları, genel başkan, gezi eylem, gezi park, gezici, gözaltı, grup toplantısı, güvenlik, haçlı, haklar, halep, Halisdemir, Halk Bank, Hamas, hanefi avcı, havuz medyası, HDP, HDPKK, hendek, hırsız, Hrant Dink, hukuk devleti, hükümet, ırkçı, İçişleri, idam, ideoloji, İdlib, ifade özgürlüğü, ihanet girişimi, ihanet şebekesi, İHH, ihraç, iktidar, ilçe teşkilatı, imar rantı, İmralı, incirlik, ingiliz, insan hakları, İran Rejimi, İsmail Saymaz, İsrail, istihbarat, istismar, işbirlikçi, işgal, İyi Parti, jitem, kahraman, kamuoyu, kandil dağı, karapara, KATAR, katliam, kayyım, kemalist, kerkük, KHK, Kılıçdaroğlu, Kızıl Elma, koalisyon, Kobani, komplo, komünist, konsolos(luk), Kudüs, kukla, kurultay, Külliye, kürdistan, kürt halkı, kürt meselesi, kürt sorunu, kürtçe, kürtler, laiklik, liberal, Lozan, mahkeme, Man adası, marksist, mason, mavi marmara, mazlum, meclis, Mehmet Altan, Meral Akşener, Mescid-i Aksa, MGK, MHP, milis

gücü, militan, milletvekili, milli görüş, milli güvenlik, milli irade, milliyetçi, Mit Tırları, montaj, Mossad, muhalefet, muhalif, Muhsin Yazıcıoğlu, musul, mülteci, Münbiç, müttefik, müzakere, Myanmar, NATO, Nazlı Ilıcak, neocon, nifak, Nuriye Gülmen, Nuriye ve Semih, Obama, OHAL, Olağanüstü Hal, operasyon, ortadoğu, otoriter, oy ver, öcalan, örgüt, ÖSO, özerklik, Özgür Suriye Ordusu, paçavra, paralel, parlamento, parti, pensilvanya, perinçek, peşkeş, peşmerge, piyon, PKK, polis, politik, propaganda, protesto, provokasyon, provokatör, Putin, Recep Tayyip Erdoğan, referandum, reis, Reisi Cumhur, rejim, Rıza Sarraf, RT\_Erdogan, Rus(ya), rüşvet, Saadet Partisi, sağcı, sahte belge, Salih Müslim, savaş, seçim, seçmen, Selahattin Demirtaş, Semih Özakça, serhildan, silivri, siyasal, siyaset, siyasi, siyonist, solcu, soydaş, soykırım, sömürü, sömürge, sözcü, suikast, Suriye, Şah Türbesi, şehit, şer odakları, şeriatçı, Tahir Elçi, TBMM, tek millet, terör sevici, terörist, torba kanun, torba yasa, troller, Trump, tutuklu, tuzak, türgev, Türk Bayrağı, Türk milleti, Türkçü, Türkes, Türkmen, uğur mumcu, usülsüz, uşaklar, uzun adam, ülkü ocağı, ülkücü, ülküdaş, vatan haini, vatandaşlık, vatansever, vatikan, vekil, vergi kaçakçılığı, yahudi, Yakup Saygılı, yandaş, yargılanma, yobaz, yolsuzluk, yönetim sistemi, YPG, yunan, Yurtta Sulh, Babek Zencani, zihniyet, zulüm.

### C. POLITICALLY CONTROVERSIAL HASHTAGS USED TO CREATE "POLITICAL DISCUSSION" VARIABLE

#10ekimkatliamınıunutmadık, #115çocuğaİstismarıörtemezsin,  
#15temmuzdarbetiyatrosu, #1915ruhuyulahayır, #1cümleileerbakananlat,  
#1kasımdaoyumhdpye, #1yıldirtutsak, #301madenciyiunuturmayalım,  
#37öğrenciyemüebbetverildi, #81İlevetdiyor, #açlıkta6aynuriyesemiheadalet,  
#adaletdedilerpkçkıktı, #adaletiçinİstanbulayürüyor,  
#adaletiçinİstanbulayürüyoruz, #adaletiçinyürüyüş, #adaletyürüyüşü,  
#afrinsavasınahayır, #afrinsavaşınahayır, #ahaberimedokunma,  
#ahabersusturulamaz, #ahlaksızkılıçdaroğlu, #ahmetaltanaözgürlük,  
#ahmetçıkacakyineyazacak, #ahmetkayabizimle, #ahmetşık, #ahmetşıkaozgürlük,  
#ahmetşıkgazetecidir, #ahmetşıkyalnızdeğildir, #akgençlikhazır, #akitelanet,  
#akitkapatılsın, #akpartidemek, #akpartigeliyor, #akpartionbeşyaşında,  
#akpartiyapar, #akpartiyidestekliyorumçünkü, #akpçocuklardaneliniçek,  
#akpİstifa, #akpsaldırıyorhdpdireniyor, #akpyekarşıeiletürkiye,  
#akpyemecburdeğiliz, #akpyeoyvermemçünkü, #akpyesoruyoruz, #aksilahlanma,  
#alışmayacağız, #aliİsmailhep19yasında, #aliİsmailhep19yaşında,  
#aliİsmailkorkmaz, #aliismailkorkmaz, #aliİsmailkorkmazİcinadalet,  
#aliismailkorkmazicınadalet, #aliİsmailkorkmazİcinadaletİstiyoruz,  
#aliİsmailkorkmazölümsüzdür, #alobabacığım, #anayasadeğişikliğinehayır,  
#ankaraevetdiyor, #arakanağlıyor, #arakandakatilamvar, #arakandakatliamvar,  
#arakannsesiol, #artvindemadencinayettir, #artvindemadenedurde,  
#artvindemadenehayır, #artvindireniyor, #artvinedokunma, #asrınliderierdoğan,  
#atatürksüzümüfredatahayır, #atatürkünpartisichp, #avrupalidergörsün,  
#aymkararıutançvericidir, #aynıgemidedegiliz, #ayşeöğretmenyalnızdeğildir,  
#babykillerdemirtaş, #babykillerturkey\_russia, #bahçelihayırdiyor,  
#bakanlaryetmez hükümetİstifa, #bakaramakaraegemen, #barışatayyalnızdeğildir,  
#barışatayyalnızdeğildir, #barışdiyenleriöldürdünüz, #başaramayacaksınız,  
#başbakanaduaediyoruz, #başçalanınbombaseskaydi, #başınsağolsuncandıındar,  
#başkanlığahayır, #başkanlığahayırdiyorumçünkü, #başkanlığahayır,  
#başkanlığınfaturası, #başkanlığınızbatsın, #başkanlıkgeliyordünyatitriyor,  
#başkanlıkığruna, #başkomutanerdoğan, #battalİlgezdisahipsizdeğildir,  
#battalİlgezdialnızdeğildir, #benaliİsmailkorkmaz, #benimkararımnet,  
#berkinelvan, #berkinelvanolumsuzdur, #berkinelvanölümsüzdür,  
#berkininkatiliyargılansın, #berkinuyanacak, #beyaztvkapatılsın,  
#birgünesahipçık, #birliktenhayirdoğar, #birmilletindirilişevet,  
#bizbittidemededenbitmez, #bizimustayağüvenimiztam,  
#bozkurttürklüğünsembolüdür, #bugünhayırçıkacak,  
#büyükkongrekutluyürüyüş, #candıındarerdemgüyalnızdeğildir,

#candündererdemgülyanlızdeğildir, #candündaryalınızdeğildir,  
#cemaatlerkapatilsin, #cerattepedireniyor, #chpedofili, #chplilernedensessiz,  
#chpmeclistençekil, #chppartideğilteröryuvası, #chpyepkklılıbaşkanı,  
#cizredekatliamvar, #cizredesivilhalkkatlediliyor, #cizreunderattack,  
#cizreyeacilsesver, #cizreyesesver, #cumhurbaşkanıerdoğan, #cumhurbaşkanımız,  
#cumhuriyeteözgürlük, #cumhuriyethalatutuklu, #cumhurunreisiyleüçüncüyıl,  
#çhdsusmadısusmayacak, #çirkefchp, #çocukİstismarcısıakp,  
#daimamilletkararımızevet, #dakika34teheryertaksimheryerdireniş,  
#dallamayusufyerkel, #darağacında3fidan, #darağacındaüçfidan,  
#darbedegiltiyatro, #darbedegiltiyatro, #dayangeziparkı, #dayangeziparkı,  
#demirtaşbizleriz, #demirtaşçoközledik, #demirtaşınyanındayız,  
#demirtaşlabuluşmaya, #demirtaşnedencezaevinde, #demirtaşonurumuzdur,  
#denizgezmiş, #devletadamıbahçeli, #devletbahçelitürkiyedir, #dictatorerdogan,  
#dikduranbaşbakanrterdoğan, #dindardeğilsapıknesil, #diplomapatladı,  
#diplomasıdasahte, #diplomasızsahtekar, #direnberkinelvan, #direngaziparki,  
#direngezi, #direngaziparkı, #direngaziparkı, #direngезiseninleyiz, #direnkobane,  
#direnlice, #direnodtüormanı, #direntaksim, #dirilişimizİçinevet,  
#diyanetkapatılsın, #diyanetkapatilsin, #diyanettenhiyanet,  
#diyarbakırdafaşistsaldırılar, #doganmedyaboykot, #doğanmedyaboykot,  
#dokunulacaksınızbeyler, #dolarıolanteröristtir, #durmakyokyoladevam,  
#dünya5tenbüyüktür, #dünyabeştenbüyüktür, #dünyaliderierdoğan,  
#dünyayıtitretenadamrte, #ekmekicinekmeleddin, #engelsiztürkiyeİçinevet,  
#ensarvakfıkapatılsın, #erdoganblockedtwitter, #erdoganblockstwitter,  
#erdoganleaderofthemuslim, #erdoganvoiceoftheoppressed,  
#erdoğana güvenimiztam, #erdoğanaoyvergeleceğineyönver,  
#erdoğanaselamnöbetedeвам, #erdoğangençlerlebaşbaşa,  
#erdoğaniçokseviyoruz, #erdoğani seviyorumçünkü, #erdoğani sizeyedirmeyiz,  
#erdoğani ölümüne, #erdoğankılıçdaroğlullecanliyaınavarmısın,  
#erdoğanasüpergüchedef2023, #erdoğanlayüreyküreğe, #erdoğanserefimizdir,  
#erdoğantarih yazıyor, #erkeksensokağadeğilkobaniyegit, #europesfearoferdogan,  
#evet, #evetbinkereevet, #evetdegülümse, #evetdetarihyaz,  
#evetdevatanasahipçık, #evetdiyeceğimçünkü, #evetgelecektir,  
#evetİçinbirnedenyaz, #evetİçinsandıklara, #evrenseledokunma,  
#fetönüngüneşiakşener, #fetönünkarargahıakp, #fıratcakıroğlu, #fıratcakıroğlu,  
#gazetecilereözgürlük, #gazeteciliksuçdeğildir, #gazzedekatliamvar,  
#gazzesiyonizmemezarolacak, #geleceğimizİçinevet, #gençlerinkararievat,  
#gençlikevetdiyor, #genelbaşkanbozuntusukk, #gezi, #gezi2yasında,  
#gezi3yaşında, #gezi4yaşında, #geziparkı, #geziparkı4yaşında,  
#geziparkıcanla başla, #geziparkı, #geziparkikonserinehayir,  
#geziprovokatörleriİşbaşında, #geziyıkılıpkışlayapılacak, #geziyihatırlat,  
#geziyiunutma, #givenuriyesemihtheirjobs, #grupyorumhalktırsusturulamaz,  
#güçlülidergüçlütürkiye, #güçlütürkiyeİçinevet, #gülmeİstifaet,

#güvenimiztamliderimizerdogan, #güzelbirgelecegeevet, #haddinibilayhanoğan,  
#haddinibilrt, #halepölüyor, #halkınevladınuriyevese Mih, #halkınkararıhayır,  
#hanisahteydi, #haydievet, #hayır, #hayırcephesibirleşin, #hayırcılarabakın,  
#hayırdahabitmedi, #hayırdahayatvar, #hayırde, #hayırdebahargelsin,  
#hayırdemiyoruzçünkü, #hayırgitmiyoruz, #hayırkazandıyskçaldı,  
#hayırlıolsunbaşkanlık, #hayıroyumukullanacağım, #hayir, #hayırçünkü,  
#hayırdehayırlıolsun, #hayırdiyeceğimçünkü, #hdpaçlıkgrevindegeberin,  
#hdponurumuzdur, #hdpyalnızdeğildir, #hepimizİçinlaikeğitim,  
#hepimizyarbaymehmetalkanız, #herseyyalanheryeryolsuzluk,  
#herşeyvetlebaşlar, #herşeyyalanheryeryolsuzluk, #heryerdeevet,  
#heryertaksimheryerdirenis, #hırsızchp, #hırsızmustafayıldızdoğan,  
#hırsızsapıkakp, #hırsızvar, #hilelisonucahayır, #hırsızvar, #hoscakalberkinim,  
#hoşçakalberkinim, #hoşgeldinnuriyegülmen, #hukuktanımayancumhurbaşkanı,  
#hukümetistifa, #hulusiakarİstifa, #hükümetimegüvenimtam, #hükümetistifa,  
#hükümetİstifa, #ialsosignfornuriyeandsemih, #İçguvenlikyasasınahayır,  
#İçguvenlikyasasınahayır, #İdamcezasıgerigelsin, #idamistiyorum,  
#idamistiyoruz, #İftiralarakarşiseninleyizreis, #İhanetantlaşmasılozan,  
#İhhterörörgütüllanedilsin, #imamasaldiranalçaktutuklansin,  
#imctvsusturulamaz, #İsrailedizçöktürenerdoğan, #İsrailindostuerdoğan,  
#İstanbulvetdiyor, #İstanbulunitedhayırdiyor, #İstifaetkılıçdaroglu,  
#İstifaetkılıçdaroglu, #İstihdamlabüyüyoruz, #İstikrarİçinoylarakolsun,  
#İstikrarİçinoylarakolsun, #İstikrarmührümüzevet,  
#İyikidoğdunalıİsmailkorkmaz, #İyikidoğdundenizgezmiş,  
#İyikidoğdundenizgezmiş, #İyikidoğdunhdp, #İyikidoğdunnuriyegülmen,  
#İyikivarsınahmetşik, #İzmirevetdiyor, #kabataşadokunma, #kadınınkararıvet,  
#kadrigürseleözgürlük, #kandırılmadınızortaktınız, #kapılarıaçreİs,  
#kararımızevet, #kararımıznetoyumuzzevet, #kararimiznetoyumuzzevet,  
#karmaeğitimİstemiyoruz, #kasetlegelendekontlagider, #kasetsiyasetibizesökmez,  
#katilakp, #katildemirtas, #katildemirtaş, #katildevlet,  
#katilgezicilerburakıöldürdü, #kayyumdarbedir, #kazadegilcinayet, #kemalİstifa,  
#kerküktenvazgeçmeyiz, #kılıçdarogluİstifa, #kılıçdaroglukandile,  
#kılıçdarogluinehaklıçikti, #killererdogan, #kobanedireniyor,  
#kobaneİcinsokağa, #kudusesahipçık, #kudusesahipçık,  
#kuduskırmızıçizgimizdir, #kudüsbizimidir, #kudusesahipçık,  
#kudüsİçinayağakalk, #kudüsİçinayaktayım, #kudüsİçinyenikapıya,  
#kudüsİslamındır, #kudüsırmızıçizgimizdir, #kudüsonurumuzdur, #kurdistan,  
#kutluyürüyüşedevam, #laikeğitimesahipçık, #laikeğitimİstiyoruz,  
#laikliğisavunmaksuçdeğildir, #laikliklutuklanamaz, #licedekatliamvar,  
#licedeyangınvar, #lozanhezimettir, #mahkemekararlarınıtanımıyoruz,  
#memleketİçinhayır, #metalgreviyasaklanamaz, #milletaşkıakparti,  
#milletçemeydanlardayız, #milletdestanyazıyor, #milletdüşmanıchp,  
#milletehizmet yolunda15yıl, #milletinpartisi14yaşında,

#milletinvekilihayırdemeli, #milliveyerliİttifak, #milyonkerehayır,  
#mittırlarındansilahçıktı, #mittırlarındansilahçıktı, #mustafakemalinaskerleriyiz,  
#müfterikemal, #müftülükyaşasıhükümsüzdür, #müftülükyaşasınahayır,  
#müftülükyaşasınaltırazımvar, #müftüresminikahkıyamaz,  
#mühürsüzoypusulasıgeçerlisayılamaz, #müminlerinbaşkentikudüs,  
#natodañçikalım, #nedarbenediktatörlük, #nedenhayırdiyorum,  
#nedenhayırçünkü, #nedenmievet, #newrozpirozbe, #nuriyeandsemihmustlive,  
#nuriyeandsemihwanttheirjobs, #nuriyegülmen, #nuriyese mihaçlıkla300gün,  
#nuriyese mihaşarsabayramolur, #nuriyese mihaşasın, #nuriyese mih,  
#nuriyese miheadalet, #nuriyese mihederhalözgürlük,  
#nuriyese mihegüveniyoruz, #nuriyese mihenefesol,  
#nuriyese miheözgürlük, #nuriyese mihialacağız,  
#nuriyese mihİçinbendeİmzalıyorum, #nuriyese mihİçinbiradımdaha,  
#nuriyese mihinaçlığınasesver, #nuriyese mihinsesiyim,  
#nuriyese mihİşeladeedilsin, #nuriyese mihİşleriniİstiyor,  
#nuriyese mihleyiz, #nuriyese mihialnızdeğildir, #nuriyese mihyargılıyor,  
#nuriyese mihyasasın, #nuriyese mihyaşasın, #occupygezi, #odtüyesahipçık,  
#ohaldesoykırım, #ohalkomisyonunerede, #ohalsiztürkiyeçünkü,  
#ohalsiztürkiyelİstiyoruz, #onlarkonusurakpartiyapar,  
#onlarkonusurakpartiyapar, #ortaktınız, #oscargoestoerdogan, #ourheroerdogan,  
#oylarhdpye, #oyumakpartiye, #oyumchpyeçünkü, #oyumuzetçünkü,  
#ölürsetenölürbaşbuğlarölmez, #öncenuriyese mih,  
#özgürgündemsusturulamaz, #özgürmedyasusturulamaz,  
#özlembitorreis geliyor, #parolasandikişaretiakpartİ, #pkknındonlastıgıchp,  
#provokatörbaşbakanİstemiyoruz, #provokatörmelihgökçek, #provokatörtayyip,  
#receptatilerdoğan, #reisavrupayıtokatladı, #reisbiznöbetteyİz,  
#reisdebizdevetdiyoruz, #reishakaret, #reisinkalkanımmillettir, #reİsiyedirmeyiz,  
#reiskırmızıçizgimizdir, #reislesonunakadar, #reisleyoladevam,  
#reismilleteemanet, #reistengeldiyse davetevet, #resminikahımmüftükıyamaz,  
#rezaletsinakp, #roboskikatliamınıunutma, #rojava, #rüşvetmemleketeİhanettir,  
#sadedediktatör, #sadedediktatör'ü, #sadedediktatöryasaklar,  
#sanageziyiiktırmayacağız, #sandıktaevetdiyerek, #sandıktahayırvar,  
#sapıkdıyanetkapatılsın, #saraydadiplomapaniği, #savaşahayır, #semihözakça,  
#senibaskanyaptırmayacağız, #senibaşkanyapacağız,  
#senibaşkanyapacağızuzunadam, #senibaşkanyaptırmayacağız,  
#seniçokseviyoruzreis, #seninleyizkılıçdaroğlu, #seniyinebaskanyaptırmayacağız,  
#seniyinebaskanyaptırmayacağız, #sevgilihükümet,  
#sezgintanrıkuluyalnızdeğildir, #sizebuülkeyiböldürmeyeceğiz,  
#sizedeşvaptırmayacağız, #sokaktahayırvar, #sodayıunutma,  
#sonkhkyokhükümdedir, #sonsözümüzet, #soykırımyalanınadurde,  
#sozcusuarsaturkiyesusar, #sözcügazetedeğilpaçavra, #suructakatliamvar,  
#surucunkatilinibiliyoruz, #suruçkatliamı, #suruçkatliamvar, #suryıkılıyor,



#süleymansoyluyalnızdeğildir, #şeddelifaşistchp, #şehitfıratçakıroğlunaadalet,  
#şeyhsaidonurumuzdur, #şeytanauymahayırde, #şeytanauymahayırde,  
#şimdiensarıkapatmavakti, #tabiikievat, #tabikievat, #tahirelçisiz2yıl,  
#tarihiyolsuzlukverüşvetskandalı, #tarikatlarıkapatılsın, #tarikatyurtlarıkapatılsın,  
#tayipİstifa, #tayipistifa, #tayyipistifa, #tayyipİstifa, #tayyipİyİkİvarsın,  
#tayyipİsanagülegüle, #tayyipİsendenutanıyoruz, #tecavüzaklandı,  
#tecavüzmeşrulaştırılamaz, #tekadamrejiminehayır, #tekdevletİçinevet,  
#tektekyargılanacaksınız, #tektepegeçiyok, #terörbahanemitingşahane,  
#terördestekçisichp, #topunuzgelsenizdeevet, #ttbninyanınadayım,  
#ttbninyanınadayız, #tuncelievatdiyor, #turkeywitherdogan, #tümkalbimleevet,  
#türkiyebaşbakanınıninyanında, #türkiyeİçinbaşkanlığıevet, #türkiyeİyİolacak,  
#türkiyekudüsİçinayakta, #türkiyeninpartisi15yaşında, #türkiyesinsenerdoğan,  
#türkmendağındaKatliamvar, #türkülerimizdemirtaşa, #türkünbaşbuğutürkeş,  
#türkütürkmilliyetçisiyiz, #tvmeradyomadokunma, #twittercensorederdogan,  
#umudunbaşkentikudüs, #ülkedematemsaraydadüğün, #ülkemiİçinevet,  
#ülkeninbekasıİçinevet, #vandalchp, #vatanaşkıylaevet,  
#vatansevermüştüşaryusuftekin, #weareerdogan, #weareerdoğan, #wearegezi,  
#wehaveerdogantheydont, #weloveerdoğan, #weloverterdogan,  
#yadevletbaşayakuzgunleşe, #yalnızdeğilsinerdoğan, #yanlızdeğilsinerdoğan,  
#yansınuriyeyıkılısınafirin, #yargılanacaksınız, #yarınİmayıstayım,  
#yarındemirtaşlayız, #yarınhayırçıkacak, #yarınıyenikapıdayız,  
#yaşadıkçatürkçüyüz, #yaşıyornuriyevemih, #yavşakseçimkurumu,  
#yenitürkiyeninbaşbakanıdavutoğlu, #yerebatsınbaşkanlığınız,  
#yerebatsinseninsarayın, #yineçaktınkemal, #yinekandırmışlaryetişin,  
#yskdiplomanerede, #yürüyüşchpninbonzaisi, #yürüyüşümüzevet,  
#yüzde100hayır, #zafercaglayanıyedirmeyiz, #zeytinağacınasadakat

## D. TURKISH SUMMARY / TÜRKÇE ÖZET

### TÜRKİYE'DE TWİTTER BAĞLAMINDA KENDİ SİYASİ GÖRÜŞÜNE YAKIN HABERLERİ TAKİP ETME VE SİYASİ KUTUPLAŞMA İLİŞKİSİ

#### Literatürde Siyasi Görüşüne Yakın Haberleri Takip Etme (Partisan Selective Exposure) Olgusu

Bireylerin siyasi partilere, liderlerine ve partililere karşı tutumlarında medyanın olumlu ve olumsuz etkileri, akademik dünyada oldukça ilgi çeken tartışmalı bir konudur. Özellikle bu siyasi tutumların kutuplaşmasında medyanın rolüne dair pek çok çalışma bulunmaktadır. Literatürde medyanın siyasal kutuplaşmadaki etkisi, birbirini tamamlayan iki farklı olgu ile tanımlanmaktadır. “Selective news exposure” olarak tanımlanan kendi siyasi görüşüne yakın haberleri takip etme olgusu, bir habere maruz kalırken seçici davranmak, kendi dünya görüşüne yakın olan haberi okumayı tercih etmek, bir bilgiye ihtiyaç duyulduğunda var olan siyasi görüşle uyumlu olan ve o görüşü pekiştiren bilgiye maruz kalmayı seçmek anlamına gelmektedir. “Selective avoidance” ise, herhangi bir bilgiye maruz kalma süreçlerinde, var olan siyasi görüşlerle çatışan ve çelişen, onlarla tezat oluşturan fikir ve bilgilerden kaçınmak, desteklenen siyasi/ideolojik fikir ve hareketler aleyhine yorum içeren haberlerden uzak durmak anlamına gelmektedir.

Bu iki olgu da, Festinger'in (1962) “bilişsel uyumsuzluk” (cognitive dissonance) teorisinden üretilmiştir. Bu teoriye göre, mevcut tutum ve görüşlerle uyumlu olan bilgilere maruz kalmak bireylerde pozitif bir duygu oluşturur. Diğer yandan, mevcut tutum ve görüşlerle çelişen bilgilere

maruz kalmak ise bireylerde psikolojik rahatsızlık ve huzursuzluk yaratır. Bu nedenlerle, birey, psikolojik huzursuzluktan uzaklaşmak için, siyasi tutumu/fikirleri ve bilişsel yapısı/davranışları arasında uyumlu olan bilgilere yönelir. Bu tezin konusu bağlamında açıklandığında, bir bilgiye ihtiyaç duyduğunda, alternatif haber kaynakları arasından, siyasi tutum ve görüşleri ile tutarlı olan haberlere maruz kalmayı tercih eder, siyasi görüşleri ile çelişen haber kaynaklarından da kaçınır.

Her ne kadar “selective exposure” olgusu, hem uyumlu bilgileri seçme, hem de uyumsuz bilgilerden kaçınmayı kapsasa da, bazı araştırmacılar, aynı görüşe sahip haber kaynaklarına maruz kalmanın, karşıt görüşe sahip haber kaynaklarına maruz kalmadan alıkoymadığını savunmaktadırlar (Garrett, 2009b; Garrett et al., 2011). Festiger’in teorisi ile ilk başta çelişiyor gibi görünen bu bulgular, daha sonra teoride yapılan revizyonlarla daha iyi açıklanır hale gelmiştir. Frey (1986), bu durum ile ilgili olarak, karşıt görüşteki bilgilere maruz kalmayı seçmenin özellikle yüksek derecede siyasi taraftarlığa (partisanship) sahip bireylerde yaygın olduğunu, bunun en önemli motivasyon unsurları arasında ise, karşıt görüşlerden haberdar olmak, onlar aleyhine argümanlar geliştirmek, savunucuları ile daha iyi tartışabilmek ve bu görüşleri çürütebilmenin yer aldığını ifade etmiştir.

Bireylerin kendi dünya görüşüne yakın ve uzak fikirleri araştırma isteğinin, siyasal iletişim ve demokratik toplum süreçleri için çok önemli sonuçları bulunmaktadır. Habermas (1989), hem tartışmalı bir konunun iki tarafındaki argümanları da kavrayabilmek, hem de demokratik yurttaşlık ve medeni bir siyasal iletişim için, karşıt görüşlere maruz kalmanın önemine vurgu yapmaktadır. Mill (1859), karşıt görüşlere maruz kalmanın, en azından birbiri ile zıt teşkil eden fikirlere empati duymayı ve hali hazırda

sahip olunan siyasi / ideolojik görüşü karşımızdaki kişilerin pencerelerinden görme fırsatı sunduğunu belirtmektedir. Gerçekten de, yapılan araştırmalar, karşıt görüşlü insanlarla kurulan medeni iletişim kanallarının, hem karşıt görüşleri daha iyi anlamayı sağladığı, hem de hep aynı fikirdeki kişilerle iletişim kuranlara nazaran bireylerin siyasi tolerans seviyelerini çok daha fazla arttırdığını göstermektedir (Diana C Mutz, 2002). Bu açılarından bakıldığında, sadece aynı görüşte olan kişilerin bulunduğu ortamlar ve haberlere maruz kalmanın, toplumsal bölünmüşlük ve kutuplaşmaya etkisi de daha iyi anlaşılmaktadır. Bu bağlamda, bu tez, bireylerin var olan siyasi görüşleri ile aynı doğrultuda görüşler içeren haberlere maruz kalmalarının, onların siyasal olarak kutuplaşmalarına ne derece etki ettiğini araştırmaktadır. Benzer şekilde, farklı ve çelişen görüşlere sahip haber sitelerine maruz kalmanın, siyasal tutumlardaki kutuplaşmayı azaltıp azaltmadığı incelenmektedir.

Teorik olarak bakıldığında, bir bilgiye ulaşma süreçlerinde kendi siyasi görüşüne yakın medya organlarını seçmek için, kişilerin var olan siyasal görüşleri ile, medya organının (gazete, TV, radyo kanalı, internet sitesi, Twitter hesabı v.s.) temsil ettiği siyasi görüşün paralel olması gerekmektedir. Geçmişteki araştırmalar, hem aynı görüşe sahip haberleri okumada, hem de çelişen görüşlere sahip haberlerden kaçınmada en önemli motivasyon unsurlarından birinin, bireylerdeki siyasal taraftarlık(partisanship) seviyesi olduğunu öne sürmektedirler (Lazarsfeld et al., 1944). Gerek deneysel çalışmalarda gerekse de anketlerde, bir kişinin bir siyasi partiye olan yakınlık derecesinin, onun o siyasi ideolojiyi temsil eden haber kaynaklarına yönelmesinde büyük etkisi olduğunu bulunmuştur (Iyengar & Hahn, 2009). Bu bulgular, aynı görüşlere maruz kalma ve beraberinde gelen kutuplaşmanın boyutu ile ilgili akademik tartışmaları da beraberinde getirmektedir. Araştırmacılar, siyasi tarafgirlik

seviyesinin istisnai olduđu, toplumdaki çođu bireyde düşük olduđu, dolayısı ile çođu bireylerin farklı görüşten haber kaynaklarını da tercih ettiđi ve daha çok siyasal olarak ılımlı bir yapıya sahip olduđunu öne sürmektedir. Bununla beraber, siyasal tarafgirlik seviyesi yüksek olan bireylerin toplumdaki ılımlı kitleleri daha fazla etkileme ve kutuplaştırma potansiyeli olduđunun da altını çizmektedirler (Markus Prior, 2013).

İnternet ortamında doğan haber kaynakları, sosyal medya ve dijital iletişim platformlarının giderek yaygınlaşması, kendilerini bir siyasal parti veya ideoloji çerçevesinde tanımlayanların ana akım medya organlarından uzaklaşıp sadece kendi görüşleri ile sınırlı haberler ve bilgiler üreten kaynaklara yöneleceđi endişelerini de beraberinde getirmiştir. Yapılan araştırmalar da bu kaygıların yersiz olmadığını göstermektedir. Tıpkı Iyengar and Hahn'ın (2009) belirttiđi gibi, dijital haber kaynaklarındaki ani artış, bu medya organlarının kendi marjinal okuyucu/izleyici kitlelerinin dikkatini çekebilme ve bu yönde yayın yapmak için birbirleriyle yarışır hale geldiđi siyasal ve ideolojik olarak ayrışmış bir bilgi ortamına yol açmaktadır. Diğer yandan, internet ortamı ile birlikte gelen çok fazla haber kaynađı seçeneđi, bireyleri kendilerine en yakın olan haber kaynađına yöneltmektedir. Reuters Haber Ajansının 2016 Türkiye raporunda, katılımcılardan %73'ünün haberlere sosyal medya platformlarından ulaştıđı, kâğıt gazetelerden haber okuma oranının ise %54'lerde kaldıđı göz önünde bulundurulduđunda (Newman et al., 2016), dijital medyanın belirtilen kutuplaşma ve siyasal ayrışmadaki rolünün ülkemiz açısından boyutları daha da endişe verici hale gelmektedir. Bir iletişim ve haber takip etme aracı olarak Twitter'a bakıldıđında, bu sosyal medya platformunun, aynı görüşten haber kaynaklarını takip etme ve karşıt görüşten olanları takip etmeme davranışları için çok uygun bir şekilde tasarlandıđı görülmektedir. Bir Twitter kullanıcısı, Twitter'da hesabı olan herhangi bir

kişi, haber kaynağı veya siyasetçiyi, “takip et” sekmesine tıklayarak takip etmekte, o andan itibaren bu kaynaklardan gelen her Twitter mesajı (tweet), takip eden kişinin ana sayfasına iletilmekte ve böylece takip eden o tweet’den haberdar edilmektedir. Diğer yandan, kişi, Twitter’da mesajlarına maruz kalmak istemediği kişiler için takip etme komutu vermemekte, böylelikle karşıt görüşe ait hesapların atmış olduğu mesajlar ve o mesajlarda yer alan fikirler, hiçbir şekilde Twitter kullanıcılarına ulaşmamaktadır. Bu açıdan bakıldığında, Twitter’ın, medyanın kutuplaştırıcı rolünü daha da körüklediği düşünülmektedir. Günümüz itibariyle ulusal anlamda habercilik yapan tüm yayın organlarının Twitter’da hesapları bulunmaktadır ve bu yayın organlarının gerek kağıt gazetelerinde, gerekse de internet sayfalarında bir haber yayınlanır yayınlanmaz, aynı haber Twitter’dan tweet olarak takipçilerine ulaştırılmaktadır. Dolayısı ile Twitter’dan haberleri takip eden bir kullanıcı, istediği medya organının tüm haberlerine anlık olarak erişim sağlayabilmektedir. Bu da, Twitter’ı haberlere anında ulaşma anlamında daha da cazip hale getirmektedir. Örneğin Twitter’da hali hazırda Hürriyet gazetesinin 4 milyondan fazla takipçisi bulunmaktadır. Habertürk ve Milliyet gazetelerinin takipçileri ise sırasıyla 4 milyon ve 2.5 milyondur. Bu rakamlar, Türkiye’de Twitter’ın haber takip etme anlamında ne kadar popüler olduğunu ortaya koymaktadır. Bu nedenle, tezde kullanılacak olan veri seti, Twitter’daki haber kaynaklarının ve ilgili diğer hesapların takipçi listeleri çekilmek suretiyle elde edilmiştir.

### **Kendi Siyasi Görüşüne Yakın Haberleri Takip Etme Olgusunun Göstergeleri**

Yapılan araştırmalar, birtakım siyasi değişkenlerin, kişinin kendi görüşüne yakın olan haberleri takip etmesini yordadığını göstermektedir.

Bunların başında, siyasi tarafgirlik seviyesi gelmektedir (Petty & Krosnick, 2014). Güçlü bir siyasi kimliğe sahip bir birey, tutumları ile çelişen bir haber veya bilgi ile karşılaştığında, bilişsel anlamda daha büyük oranda uyumsuzluk yaşar ve bu uyumsuzluk ve psikolojik rahatsızlık, bireyi bahse konu haberden kaçınmaya iter (Knobloch-Westerwick & Jingbo Meng, 2009). Bir kişinin siyasete ve siyasi konulara olan ilgisi de kendi siyasi görüşüne yakın haberleri takip etmesini yordamaktadır. Kişinin siyasete olan ilgisi arttıkça, mevcut tutumunu güçlendirecek yönde daha fazla bilgi sahibi olmak ister, bu da onu kendi siyasi görüşüne yakın haberleri daha fazla okumaya/izlemeye iter. Bireyin medyayı haber takip etme açısından ne yoğunlukta ve sıklıkta kullandığı, siyasi faaliyetlere katılım oranı, hem dış dünyada hem de internette farklı fikirde olanlarla ne oranda siyasi tartışmalara girdiği, siyaset bilimi hakkında ne ölçüde bilgi sahibi olduğu, ideolojik ve siyasi olarak mevcut tutum ve görüşlerinin ne kadar sabit ve güçlü olduğu, ve yaşanan toplumdaki medya sisteminin ne kadar partizan ve ayrılmış olduğu gibi değişkenler de literatürde, kendi siyasi görüşüne yakın haberleri takip etme olgusu ile ilişkili bulunmaktadır.

### **Kendi Siyasi Görüşüne Yakın Haberleri Takip Etme Olgusunun Demokrasi ve Siyaset Bilimine Potansiyel Etkileri**

Yapılan çoğu araştırma, özellikle internet ortamında yayın yapan haber kaynaklarının, kendi siyasi görüşüne yakın haberleri takip etmeyi motive ettiği ve bunun bir sonucu olarak toplumda siyasi kamplaşma ve kutuplaşmalara etki ettiğini göstermektedir. Aynı görüşe sahip haber kaynaklarını takip ederek elde edilen bilişsel uyumun, farklı fikirlere arkasını dönerek kamudaki muhtelif kesimlerle kurulacak iletişime feda edildiği bir toplumda, her kesimin fikirleri ile uyumlu haberleri takip etmek suretiyle mevcut olan fikir ve siyasi pozisyonlarını koruyacağı ve bu

durumun demokratik toplumlardan beklenen gelişim ve değişimin önünü tıkadığı belirtilmektedir (Mutz & Martin, 2001). Bu konuda Sunstein (2007), özellikle günümüzde online medya platformlarının teşvik ettiği aynı-görüşten haber takibinin, farklı görüşler ihtiva eden bilgilere ulaşımı engellediği ve bu durumun siyasi tutum aşırılığı, kutuplaşma, toplumsal nefret ve hatta şiddeti besleyebileceği konusunda uyarılarda bulunmaktadır. Bimber and Davis de (2003) benzer bir şekilde aynı-görüşten medya seçiciliğinin insanların içinde sadece benzer siyasi görüşte insanlarla iletişime geçeceği birbirinden kopuk sosyal kümeler ortaya çıkaracağı ve sadece aynı görüşten haberleri takip etmenin bu kümeler arasındaki bağları daha da aşındıracağını söylemektedir. Türkiye’de kendi siyasi görüşüne yakın haberleri takip etme olgusu, siyasi kutuplaşma ve ilkinin ikincisine olan etkisine yönelik literatür eksikliği, bu potansiyel tehlikenin araştırılmasını daha da önemli hale getirmektedir. Bu nedenle, bu tez, a) Twitter’da ulusal yayın yapan haber kaynakları ve b) meclisteki dört büyük partinin ve milletvekillerinin resmi Twitter hesaplarının tüm takipçi listeleri çekilmek suretiyle, bahse konu araştırma sorusuna cevap aramaktadır.

### **Siyasi Kutuplaşma**

Literatürde siyasi kutuplaşma, bireylerin destekledikleri siyasi görüş, parti veya liderlerine olan tutumlarının derecesi ile, muhalif gördükleri görüşlere, partilere veya liderlerine olan tutumlarının derecesi arasındaki farkı ifade etmektedir. Diğer bir deyişle, tam anlamıyla siyasi bir kutuplaşmadan söz edebilmek için, bireyin kendisine yakın gördüğü siyasi parti/hareketlere karşı maksimum pozitif siyasi tutum duyması, aynı zamanda karşıt parti/hareketlere karşı da maksimum negatif tutum sergilemesi söz konusu olmalıdır (Tsfati & Chotiner, 2016). Bu nedenle, pek



çok akademisyenin yaptığı gibi, siyasi kutuplaşma, katılımcıların hem kendisine yakın hissettiği partiye olan yakınlık derecesi, hem de diğer partilere olan yakınlık derecesi arasındaki fark üzerinden ölçülmektedir (bkz. Stroud, 2010).

### **Siyasi Kutuplaşmanın Boyutları**

Siyasi kutuplaşmanın iki farklı boyutu bulunmaktadır. Elit kutuplaşması, siyasi parti veya hareket içindeki elitlerin/parti içinde söz sahibi olan nüfuzlu kişilerin kutuplaşmasını ifade etmektedir. Toplumsal kutuplaşma ise, toplumdaki bireylerin kutuplaşmış siyasi tutumlarını ifade eder. Yapılan araştırmalar, elitlerin aşırı siyasi tutumlarının, toplumun tutumlarının kutuplaşmasına etki ettiğini bulmuşlardır (örn: Abramowitz & Saunders, 2008).

### **Siyasi Kutuplaşmanın Göstergeleri**

Toplumda var olan siyasi kutuplaşmayı ölçmeye yarayan birtakım göstergeler bulunmaktadır. Bunların başında partilere yönelik (partisan) kutuplaşma gelmektedir. Bir kişinin partisine olan bağlılık gücü arttıkça, siyasi kutuplaşma seviyesi de artmaktadır (Gentzkow, Matthew, 2016). Yapılan araştırmalar hem Amerika'da hem de Türkiye'de, partilere olan yakınlık ve uzaklık açısından kutuplaşma seviyelerinin oldukça yüksek olduğunu göstermektedir. Örneğin, partililerin kendi parti liderlerine olan yakınlık derecesi, AKP lideri Erdoğan için %85, CHP lideri Kılıçdaroğlu için %50, HDP lideri Demirtaş için %82 ve MHP lideri Bahçeli için %45'dir. Ne var ki, partililerin diğer parti liderlerine olan yakınlık derecesi, hiç bir lider için %5'i geçmemektedir (Institutional Social Responsibility Organisation, 2016).

Siyasi kutuplaşmanın diğer bir göstergesi ideolojik görüş ayrılıklarıdır. Bir siyasi partinin temsil ettiği ideoloji, parti destekçisinin o ideolojiye olan bağlılığını da güçlendirmekte, partinin temsil ettiği ideolojinin muhalifi olan ideolojilere karşı da uzaklaştırmaktadır. Dolayısıyla, ideolojik eğilimler de partizan tutumlara etki eder. Bazı araştırmalar, ideolojik kutuplaşmanın, partilere yönelik kutuplaşmalara oranla siyasi kutuplaşmayı daha iyi ölçtüğünü öne sürmektedirler (Garrett et al., 2011).

Siyasi kutuplaşmayı ölçmeye yarayan diğer göstergeler ise sırasıyla a) tartışılabilir konulara ilişkin takınılan tutumlar ve b) parti ve yöneticilerine yönelik olumlu ve olumsuz duyguların polarizasyonudur. Kamuoyunda çokça tartışılan siyasi konular karşısında takınılan tutum, kutuplaşma hakkında bilgiler içermektedir. Benzer şekilde, desteklenen ve muhalif olunan partiler, bunların destekçileri ve temsilcilerine yönelik duygusal tepkiler de, siyasi kutuplaşmayı ölçmek için kullanılan araçlardandır.

### **Kendi Siyasi Görüşüne Yakın Haberleri Takip Etmenin Siyasi Kutuplaşmaya Etkileri**

Bireyler siyasal aidiyetlerini politik görüşleri ile uyumlu haber okuyarak güçlendirdikçe, siyasi kutuplaşma eğilimleri de artmaktadır. Yapılan araştırmalar, bu şekilde tek yönlü bilgi/haber edinme süreçlerinin, siyasi tarafsızlık ile aşırı radikalizm arasında aracı rolü oynadığını göstermektedir. Dahası, demokratik toplumlarda kamusal iletişim için hayati rolü bulunan siyasal tartışmalar ve farklılıkların, sadece tek yönlü haber okuyan kişiler söz konusu olduğunda, tam tersi bir etki oluşturduğu görülmüştür (D. C. Mutz, 2006). Normalde var olan aşırı radikal görüşleri yumuşatması beklenen bu müzakereler, sadece kendi fikirleri ile tutarlı medya organlarını takip eden kişiler tarafından gerçekleştirildiğinde daha fazla kutuplaşmaya yol açmaktadır (Knobloch-Westerwick & Jingbo Meng,

2009). Özellikle sosyal medya uygulamalarının teknolojik algoritmalar ile kişilerin siyasi görüşlerini tahmin etmesi ve karşlarına o görüşe uygun haberler sunması, dijital ortamlarda birbirleri ile çatışan grup aidiyetleri ve yankı odaları (echo chambers) oluşmasına neden olmaktadır. Sunstein'ın (2007) dediği gibi, bu homojen yankı odaları içerisinde bilgilere maruz kalmak, daha önce var olan siyasi tutumları, aynı doğrultuda aşırı uçlara yaklaştırmakta ve böylece daha da kutuplaştırmaktadır. Diğer yandan, aynı görüşten haber kaynaklarını takip etmek, bireylerin siyasi argümanlara olan aşinalığını daha da arttırmakta, ve bu argümanları sürekli zihninde saklamasına neden olmaktadır (Gvirsman, 2014). Dolayısı ile, sürekli aynı görüşten haberlere maruz kalmak, kişilerin bu argümanlara daha fazla bağlanmasını ve onları siyasi görüşlerinde temel dayanak noktası haline getirmesine neden olmaktadır.

Tüm bu bulgulardan yola çıkarak, bu tez, Türkiye'de Twitter örneğinde kendi siyasi görüşüne yakın haberleri takip etme ve siyasi kutuplaşmanın çok yüksek olduğunu iddia etmektedir. Spesifik olarak, Twitter'daki kullanıcıların, büyük oranda kendi görüşlerine yakın haber sitelerini takip etmelerini, karşıt görüşten siteleri takip etmekten kaçınmalarını beklemektedir. Ayrıca, kutuplaşmanın bir göstergesi olarak kullanıcıların, sadece kendi siyasi partilerini temsil eden milletvekillerini Twitter'da takip etmelerini, karşıt görüşlü partilerin vekillerine ait hesapları takip etmemelerini beklemektedir. Son olarak, tezin ana hipotezi, Twitter'da sadece kendi siyasi görüşleri ile uyumlu olan haber sitelerini takip etmenin, siyasi kutuplaşmaya etki edeceği yönündedir. Hipotezin diğer bölümünde ise, Twitter'da karşıt görüşlü haberleri takip etmenin, kutuplaşma eğilimlerini azaltacağı savunulmuştur.

## Veri Seti ve Metot

Bir Twitter kullanıcısının politik görüşleri ile uyumlu haberleri takip etme derecesini ölçebilmek için, a) Twitter kullanıcılarının siyasi parti eğilimleri b) Twitter veri setinde bulunan haber sitelerinin siyasi parti yakınlıkları c) her bir kullanıcının kendi partisine yakın ve uzak olan haber sitelerini ne oranda takip ettiğinin incelenmesi gerekmektedir.

Bu nedenle, öncelikle ulusal anlamda yayın yapan ve Twitter'da hesabı bulunan toplam 53 haber sitesi tespit edilmiştir. Daha sonra, bu 53 haber kaynağının tüm takipçi listesi Twitter'da REST API uygulaması yardımıyla ve Python programlama dili kullanılarak toplanmıştır. Bu bağlamda, toplamda 30.085.033 takip ilişkisi veritabanına aktarılmıştır. Twitter kullanıcılarının siyasi eğilimlerini belirleyebilmek amacıyla, mecliste koltuğu bulunan 4 büyük siyasi partinin Twitter hesabı ve yine bu partilerin vekillerinin mevcut hesapları (AKP = 285, CHP = 126, HDP =49, MHP =33) tespit edilmiş ve indirilmiştir. Toplamda, bir Twitter kullanıcısından en az bir milletvekiline veya parti resmi hesabına çıkan 78.917.555 takip ilişkisi veri tabanına kaydedilmiştir. Her iki veri tabanı birleştirilince, Twitter'da toplam 21.418.717 farklı kullanıcı kaydedildiği görülmüştür. Hem tezin konusu olan siyasi görüşlerle tutarlı haber seçiciliği ve kutuplaşma ilişkisine yoğunlaşabilmek, hem de analizleri daha kolay yapabilmek amacıyla, ikiden az haber sitesi ve ikiden az vekil/parti hesabı takip edenler veri tabanından çıkarılmıştır. Böylelikle veri setinde toplamda 2.790.339 tekil kişiye ait 48.316.548 takip ilişkisi kalmıştır. Tüm analizler, bu veriler üzerinden yürütülmüştür.

Haber sitelerinin siyasi partilere olan yakınlıkları, veri setindeki a) her bir haber sitesinin diğer haber sitesi ile arasındaki ortak takipçilerine

göre kümelenmesine ve b) her bir haber sitesinin her bir parti/milletvekili ile ortak takipçilerine göre kümelenmesine bakılarak belirlenmiştir. Bu aşamada Sosyal Ağ Analiz araçları kullanılmıştır. Spesifik olarak, 53 haber sitesinin siyasi olarak birbirine olan yakınlık ve uzaklık oranı, kendi aralarındaki ve parti/vekillerle aralarındaki ortak takipçilerinin rakamları baz alınarak ki-kare yakınlık ölçümüne göre belirlenmiş, daha sonra da bu değerler Phi değerlerine dönüştürülerek standartlaştırılmıştır. Pajek (Batagelj & Mrvar, 1998) isimli uygulama içerisinde Louvain (Blondel, et al., 2008) isimli kümeleme metodu kullanılarak, Phi değerleri üzerinden medya grupları ortaya çıkarılmıştır. Ayrıca her bir medya grubunun hangi parti ile yakınlaştığı da bu bağlamda tespit edilmiştir.

Kümeleme analizi ile partilere yakınlıklarına göre gruplandırılan haber sitelerinin alt kümelerini ortaya çıkarabilmek için, louvain metodunda daha yüksek ayrıştırma (resolution) parametreleri kullanılmıştır. Bu sayede, her iki ayrı analiz sonucu, birbirini kapsayan ve siyasi partilerle ilişkili 3'er farklı medya grubu ortaya çıkarılmıştır. Bu analizler sonucunda, hem haber sitelerinin kendi aralarındaki ortak takipçi analizi ile ortaya çıkan gruplar, hem de haber sitelerinin milletvekili hesapları ile aralarındaki ortak takipçi analizi ile ortaya çıkan gruplar arasında yüksek bir korelasyon olduğu görülmüştür. Tüm kümelerde aynı partilerin etrafında toplanan haber siteleri o partilerle ilişkilendirilmiştir. Bazı kümelerde bir parti ile doğrudan ilişkili görülen, fakat diğer kümelerde ise o partiye yakın fakat tam olarak o parti kümesi içerisinde yer almayan siteler ise, o partiye meyilli (leaned) olarak kodlanmıştır. Hiçbir partiye yakın görünmeyen siteler ise, belirsiz/ılımlı şeklinde kodlanmıştır. Bu şekilde, tüm siteler ya bir siyasi parti ile doğrudan ilişkili, ya o partiye meyilli, ya da belirsiz/ılımlı şeklinde gruplandırılmıştır.

## **Twitter Kullanıcılarının Siyasi Eğilimlerinin Belirlenmesi**

Literatürde geçmişte yapılan araştırmalardan yola çıkılarak, bir kişinin Twitter’da en çok takip ettiği siyasi parti milletvekillerinin, kişinin o partiye yakınlık göstergesi olduğu varsayılmış, buradan hareketle veri tabanındaki 2.790.339 Twitter kullanıcısının her birinin, veri tabanındaki 493 milletvekili ve 4 siyasi partinin Twitter hesaplarını takip etme ilişkisi incelenmiştir. Bu analizler sonucunda, her bir kullanıcı, 4 partiden en çok takip ettiği milletvekilinin partisi ile ilişkilendirmiştir. Kişinin milletvekili takip sayısına göre, partisi ile yakınlık ilişkisi 1) güçlü 2) orta derece,3) zayıf ve 4) meyilli olarak kodlanmıştır. En çok takip ettiği iki partiye ait vekil sayısının eşit olması durumunda ise, kullanıcı ılımlı olarak kodlanmıştır.

## **Siyasi Görüşlerle Uyumlu Haber Seçiciliğinin Ölçümü**

Hem haber sitelerinin hem de onları takip eden Twitter kullanıcılarının siyasi eğilimi belirlendikten sonra, bir Twitter kullanıcısının siyasi görüşleri ile tutarlı haber seçicilik indeksi, kendi partisine yakın medya kümesinden takip ettiği haber sitesi sayısının, diğer partilere yakın medya kümelerinden takip ettiği sitelerin toplamına bölünerek hesaplanmıştır. Medya kümelerinde eşit sayıda haber sitesi bulunmadığından, ortak katların en küçüğü (okek) ile bu indeksler standartlaştırılmıştır. Bu sayede, her bir kullanıcının, 0 ile 100 arasında değişen bir aynı-görüşte haber seçicilik indeksi oluşturulmuştur.

Twitter kullanıcılarının siyasi kutuplaşma indeksi ise, yine literatürdeki geçmiş çalışmalardan yola çıkılarak, bir kullanıcının kendi partisine olan yakınlık oranı ile, diğer partilere olan yakınlık oranı arasındaki fark üzerinden hesaplanmıştır. Yakınlık oranı ise, her bir

kullanıcının partisinden kaç milletvekili takip ettiğine göre belirlenmiştir. En çok milletvekili takip edenler en yakın, en az vekil takip edenler en az yakın olarak kodlanmıştır. Her 4 partide de farklı sayıda vekil bulunduğundan, indekslerin standartlaştırılması adına her parti için üç çeyreklik (three quartile) analizi yapılmış, takip etme sayısına göre ilk çeyrek, orta çeyrek ve son çeyrek içerisinde yer alan kullanıcılar, partileriyle sırasıyla en yakın (strong), orta yakın (moderate) ve en az yakın (weak) olarak ilişkilendirilmiştir.

Hem siyasi görüşlerle uyumlu haber seçicilik indeksi hem de kutuplaşma indeksi oluşturulduktan sonra, öncelikle her iki değişkenin de partilere göre oranları incelenmiştir. Sonuçlara bakıldığında, Twitter'daki tüm partililerin çok yüksek oranlarda kendis siyasi görüşleri ile uyumlu haber seçiciliği ve siyasal kutuplaşma oranlarının bulunduğu, kişinin partisine olan yakınlık oranı arttıkça bu iki değişkenin arttığı, azaldıkça bu değişkenlere ait skorların da azaldığı görülmüştür.

İki değişken arasındaki ilişkiyi incelemek için, twitter veri setinde bazı kontrol değişkenleri üretilmiştir. Literatürde en çok kullanılan, 1) siyasi tartışma, 2) siyasete olan ilgi, ve 3) Twitter'ı kullanma yoğunluğu sayısal verilere dönüştürülmüş ve bunlar yapılacak olan regresyon analizinde kontrol değişkeni olarak kullanılmıştır. Ayrıca, siyasi görüşleriyle uyumlu haber seçiciliği birbiri ile bağlantılı iki değişkeni birden (siyasi taraftarlık (partisanship) ve haber seçiciliğini (selective exposure)) ilgilendirdiğinden, regresyon analizine, önce bu değişkenler ayrı ayrı sokulmuş, daha sonra da bu iki değişken etkileşim terimi (interaction term) olarak birlikte analize eklenmiştir. Böylelikle, bir twitter kullanıcısının, tüm siyasi partilere olan siyasi eğilim indeksi ve yine tüm

parti-ilişkili medya kümelerine olan seçicilik indeksi etkileşime sokularak regresyon analizi yapılmıştır.

Sonuçlara bakıldığında, tüm partililer için, bir partiye olan yakınlık ve o partiye yakın haberlerin takip etmenin birlikte etkileşime girerek siyasi kutuplaşmayı etkilediği ve yordadığı görülmektedir. Diğer bir deyişle, bir partiye olan aidiyet duygusu daha güçlü olan Twitter kullanıcıları, o partiye yakın olan haber sitelerini takip ettikçe, daha fazla siyasal olarak kutuplaşmaktadır. Tam tersi olarak, bir partiye olan aidiyet duygusu ne kadar güçlü olursa olsun, partisinin görüşlerini temsil etmeyen haber sitelerini takip eden kullanıcıların ise çok daha düşük seviyelerde kutuplaşma indekslerinin olduğu görülmektedir. Bu sonuçlar, tüm partililer için benzer seviyelerdedir. Analiz sonuçları, tezin ana hipotezi olan, kendis siyasi görüşüne yakın haberleri seçme olgusu ile kutuplaşma arasındaki ilişki olduğu varsayımını istatistiksel olarak güçlü bir şekilde doğrulamıştır.

Tezde kullanılan ölçümlerin doğrulanması amacıyla, hem siyasi partilere olan yakınlık endeksi, hem de siyasi kutuplaşma endeksi için veri setinden farklı ölçümler kullanılmış ve tezdeki ölçümlerle uyumlu olup olmadığına bakılmıştır. Siyasi partilere olan yakınlık için, tez veri seti içerisindeki kullanıcılardan rastgele olarak 45.880 kişilik bir örneklem seçilmiş, bu kişilerin en son 3.200 tweeti Python program aracılığıyla Twitter'dan çekilmiştir. Bu kişilere ait yaklaşık 5 milyon tweet çekilmiş ve her bir tweet içerisinde kaç tane "AKP", kaç tane "AK PARTİ" gelimesinin geçtiği SQL sorgularıyla hesaplanmıştır. Hesaplamalar sonucunda, ilk ölçümde partilere yakınlık oranı çeşitli seviyelerde hesaplanan grupların twitlerinde, Adalet ve Kalkınma Partisi'ni ifade eden hangi kelimenin daha fazla geçtiğine bakılmıştır. Yapılan analizler sonucunda, ilk ölçümde



AKP'ye yakınlık oranı güçlü olarak belirlenen Twitter kullanıcılarının %93'ünün tweetlerinde ağırlıklı olarak "AK Parti" ifadesinin geçtiği, CHP ve HDP'ye yakınlık oranı güçlü olarak belirlenen kullanıcıların ise, sırasıyla %93 ve %97'sinin tweetlerinde ağırlıklı olarak "AKP" ifadesinin geçtiği görülmüş, dolayısı ile tezde kullanılan ölçümün doğruluk testi yapılmıştır.

Kutuplaşma indeksinin doğruluk testi ise, yine yukarıda belirtilen 45.880 kişilik örneklem grubunun en çok retweetlediği 500 siyasi hesap üzerinden gerçekleştirilmiştir. Daha açık bir ifadeyle, öncelikle bu 500 hesap tek tek incelenmiş ve "hükümet yanlısı" ve "hükümet karşıtı" olarak kategorilendirilmiştir. Daha sonra da, literatürde kullanılan başka bir kutuplaşma indeksi olan, her bir kullanıcı tarafından hükümet yanlısı hesapların retweet edilme oranı ile hükümet karşıtı hesapların retweet edilme oranı arasındaki fark, alternatif siyasi kutuplaşma indeksi olarak oluşturulmuştur. Yapılan analizlerde, retweet oranlarına göre belirlenen kutuplaşma indeksinin de, tezde kullanılan kutuplaşma indeksi gibi her parti grubu için çok yüksek oranda çıktığı gözlemlenmiştir (AKP: %87, CHP: %83, HDP: %93, MHP: %64).

Son olarak, aynı siyasi görüşten haber seçiciliği ile kutuplaşma değişkenleri arasındaki ilişki, bu alternatif kutuplaşma indeksi kullanılarak tekrar regresyon analizine sokulmuş ve analiz sonucunda, tüm partiler için siyasi görüşlerle tutarlı haber seçiciliği ile kutuplaşma arasında, önceki regresyon analizinde olduğu gibi, istatistiksel olarak anlamlı sonuçlar bulunmuştur.

Bu tez, hem tamamen yeni ve özgün bir veri seti kullanması, hem de Türkiye'de ilk defa siyasi görüşlerle uyumlu haber seçiciliği, kutuplaşma ve ikisi arasındaki ilişkiyi bilimsel bir şekilde ortaya koyması açısından literatüre önemli katkılar sunmaktadır. Ayrıca literatürde çok partili

sistemlerde aynı-görüşten haber seçiciliğini tüm partililer için özgün bir metotla ölçen ilk çalışma olduğu düşünülmektedir.

Twitter'daki milyonlarca kullanıcının siyasi taraftarlık, sadece kendi görüşüne yakın haberleri takip etme ve kutuplaşma seviyelerindeki oldukça yüksek oranlar göz önünde bulundurulduğunda, tezdeki bulguların Türkiye'deki kamusal/siyasal iletişim ve demokratikleşme süreçleri için kaygı verici olduğu görülmektedir. Dolayısı ile bu sonuçlar hem akademisyenler hem psikologlar, hem de siyasi karar alıcılar için önemli anlamlar ifade etmektedir.

Tezdeki bulgular, sadece Twitter popülasyonuna ait sonuçlardır ve tüm Türkiye toplumuna doğrudan genellenmesinde sakıncalar bulunmaktadır. Diğer yandan, tezin en önemli eksikliklerinden biri, - *Twitter'daki veriler bu tarz kişisel bilgiler içermediğinden*- regresyon analizi için yaş, cinsiyet, eğitim, gelir durumu gibi demografik değişkenlerin kullanılmamış olmasıdır. Bu eksik değişkenler, Twitter'da tespit edilen siyasi taraftarlık, aynı-görüşten haber takibi ve kutuplaşma seviyelerinin hangi demografik gruplarda daha yoğun olduğuna dair analizlerin önüne geçmiştir. Dolayısı ile, bu demografik değişkenler olmadan, tespit edilen bulguların tüm Twitter kullanıcıları için mevcut olduğunu söylemek de zorlaşmaktadır.

Tezdeki önemli eksikliklerden bir diğeri de, regresyon analizi için kullanılan verinin tek zamanlı ve kesitsel bir veri olduğu ve dolayısı ile değişkenler arasında bir sebep-sonuç ilişkisi kurulmasına imkan vermemesidir. Her ne kadar geçmiş araştırmalardan yola çıkarak kendi siyasi görüşüne yakın haber seçiciliğinin siyasi kutuplaşmaya neden olduğu varsayılsa da, Türkiye örneğinde bu nedensellik ilişkisi ve yönünün somut bir şekilde ortaya konulabilmesi için boylamsal

(longitudinal) arařtırmalara ihtiya duyulmaktadır. Son olarak, tezde siyasi fikirlerle uyumlu haber seicilięi iin sadece Twitter'da hesabı bulunan haber siteleri incelenmiřtir. Gelecek alıřmalarda, kiřilerin kâğıt gazeteler ve televizyon/radyo programlarına dair tercihleri arařtırılarak, aynı siyasi grüşten haber takip etme aısından internet dnyası ile evirim dıřı dnya arasında bir fark olup olmadıęının belirlenmesi faydalı olacaktır.

## E. TEZ FOTOKOPİSİ İZİN FORMU

### ENSTİTÜ

Fen Bilimleri Enstitüsü

Sosyal Bilimler Enstitüsü

Uygulamalı Matematik Enstitüsü

Enformatik Enstitüsü

Deniz Bilimleri Enstitüsü

### YAZARIN

Soyadı : Gölcük

Adı : Seyit

Bölümü : Siyaset Bilimi ve Kamu Yönetimi

**TEZİN ADI** (İngilizce) : Partisan Selective Exposure and Polarization on Twitter Networks in Turkey

**TEZİN TÜRÜ** : Yüksek Lisans

Doktora

1. Tezimin tamamı dünya çapında erişime açılsın ve kaynak gösterilmek şartıyla tezimin bir kısmı veya tamamının fotokopisi alınsın.

2. Tezimin tamamı yalnızca Orta Doğu Teknik Üniversitesi kullanıcılarının erişimine açılsın. (Bu seçenekle tezinizin fotokopisi ya da elektronik kopyası Kütüphane aracılığı ile ODTÜ dışına dağıtılmayacaktır.)

3. Tezim bir (1) yıl süreyle erişime kapalı olsun. (Bu seçenekle tezinizin fotokopisi ya da elektronik kopyası Kütüphane aracılığı ile ODTÜ dışına

Yazarın İmzası:

Tarih: