Subsidizing the Messenger: How Connected Owners Shape Economic News

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Scholars have extensively investigated the interest of incumbents in controlling media and the role of financial independence in safeguarding press freedom. Nonetheless, the literature lacks evidence on how governments employ ostensibly legal methods to fund connected media in exchange for favorable coverage. This paper identifies market-based exchanges as two-way favors between the government and politically connected media owners, exploiting the acquisition of the largest media company in Turkey by a pro-government conglomerate in 2018. First, I find sizable advertising favors from the government as the 2018 sale significantly increased state advertising in the acquired newspapers, despite a simultaneous decline in their circulations and private advertising. Second, these newspapers return the favor with biased economic news supportive of the government. My results establish that state advertising in Turkey is politically driven and incompatible with economic incentives, and the connected newspapers cater to the government, potentially at the expense of circulation.

Keywords: Media capture, government advertising, politically connected owners, triple-differences regression, topic modeling, sentiment analysis, BERT, GPT

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1 Introduction

The financial independence of media outlets is quintessential to free and high-quality journalism that provides citizens with information to keep their governments accountable and take political action in their best interest. As a vast source of income in the media industry, advertising revenues received a substantive amount of scholarly attention in media capture literature. Besley and Prat (2006) mention advertising as a source of audience-driven commercial profit for media, which makes it more costly for the government to capture the outlets, i.e., to offer "a transfer in exchange for silence". Similarly, where advertising revenues are high, media outlets are less likely to be affiliated with political parties (Petrova, 2011) and less likely to provide pro-government bias as the audience prefers news covering the truth (Gehlbach and Sonin, 2014). Another line of literature focuses on the political effects of media and government's strategies to manipulate news coverage. Studies provide extensive evidence on the persuasion and electoral influences of editorial and partisan slant (Benedictis-Kessner et al., 2019; Druckman and Parkin, 2005; Martin and Yurukoglu, 2017; Peisakhin and Rozenas, 2018), the impact of economic news on voting decisions (Garz and Martin, 2021), and the manipulation of economic news to portray incumbent leaders as more competent than challengers (Adiguzel, 2025; Guriev and Treisman, 2020; Rozenas and Stukal, 2019).

Are advertising revenues always audience-driven and conducive to press independence? This paper shows evidence that transfers to media outlets from the government can take the form of advertising funds, and outlets receiving such transfers bias their economic news to provide more favorable coverage to the government. Hence, it contributes to the growing literature concerning that governments can use state advertising to capture media (Di Tella and Franceschelli, 2011; Szeidl and Szucs, 2021). Conditional on its size relative to private advertising, state advertising[1] can offset outlets' loss of income due to reduced audience and

[1] According to the 2022 proposal amending European Media Freedom Act, state advertising "should be understood broadly as covering promotional or self-promotional activities undertaken by, for or on behalf of a wide range of public authorities or entities, including governments, regulatory authorities or bodies as well

make it more profitable for the outlets to accept transfers from the government, thereby substantially influencing news coverage. Di Tella and Franceschelli (2011) show that newspapers in Argentina that received more government advertising placed significantly less coverage of corruption scandals on their front pages, even though hiding the corruption stories reduced their circulation. Moreover, the government has incentives to dominate the media advertising by abusing public resources to increase its influence on news coverage. In support of this argument, Levitsky and Way document that the Peruvian government in the late 1990s doubled the state advertising expenditures and became the leading advertiser in the country during the economic slowdown when advertising revenues dropped (Degregori, 2000; Youngers, 2000, as cited in Levitsky and Way (2010)). In addition to creating affiliated media, the government can use its position as a major advertiser to lower the capacity of independent media to produce high-quality journalistic content to effectively impede people from receiving politically relevant information[2].

Tilting state advertising funds towards the pro-government media can be considered as an ostensibly legal and arguably low-risk method of capturing media compared to banning the outlets or engaging in clearly illegal transactions such as distributing bribes specifically in contexts with some democratic institutions such as competitive elections, where incumbents have re-election concerns and avoid public outcry. However, whether governments use such market exchanges[3] to capture media is relatively under-explored within a causal identification framework. Szeidl and Szucs (2021) review academic studies and media reports that suggest the existence of politically-targeted state advertising in 17 countries, where the state is arguably a major advertiser in the media in 15 of them[4]. Although it appears to be a

as state-owned enterprises or other state-controlled entities in different sectors, at national or regional level, or local governments of territorial entities of more than 1 million inhabitants." (Source: eur-lex.europa.eu)

[2]Angellucci and Cage (2019) find that advertising revenues are consequential to news production. Between 1960 and 1974, a reduction in advertising revenues of French national newspapers due to the introduction of TV advertising decreased the amount of their journalistic-intensive content significantly.

[3]Studies on market-based sources of media capture and media bias also concern the influence of non-government actors such as private advertisers (Beattie et al., 2020; Beattie, 2020) and the rich (Petrova, 2008), and the effects of readers' preferences (Gentzkow and Shapiro, 2010) and profit maximization by journalists and news organizations (Baron, 2006).

[4]These countries are Bulgaria, Greece, Hungary, Poland, Romania, Slovakia, Slovenia, Albania, Mace-

prevalent problem that could affect millions of people's access to information, existing studies provided mostly correlational or suggestive evidence lacking a rigorous causal framework to identify the effect of political incentives in the allocation of state advertising. Identifying state advertising allocations as political *favors*[5] requires an empirical strategy that accounts for target audiences and economic incentives to advertise. To my knowledge, Szeidl and Szucs (2021)'s study on Hungary is the only academic study that identifies advertising favors in media markets by rejecting conventional market-based choices for platforms.

The current paper differs from their study as I focus on the supply side of ads to show how state-owned enterprises (SOEs) deviate from solely audience-driven advertising behavior. Using text analysis, I conduct a thorough analysis of ads advertised by private and state-owned enterprises to establish that they promote similar products using a similar language, which suggests a common target audience for the promoted products and a shared commercial incentive to advertise in the same outlets. Since I compare ads essentially similar in terms of their contents, unlike the reduced-form analysis in Szeidl and Szucs (2021), the identification of advertising favors does not rely on audiences not to change within a short time around the treatment, as any audience change should affect the state-owned and private advertisers equivalently. Then, I exploit the changes in media outlets' connections to the government in a triple difference regression (DDD) design using private advertising as a "placebo stratum" to difference out the economic incentives of state-owned advertisers from the treatment effect. More specifically, the causal parameter of the DDD design identifies politically motivated advertising allocations to the connected media outlets because it is the difference between the treatment effects in "primary" DD (state advertising) and the "placebo" DD (private advertising) (Olden and Møen, 2022; Strezhnev, 2023), and I rely on the assumption that private advertisers do not have the political incentives to favor media outlets connected to the government.

donia, Serbia, Turkey, Argentina, Brazil, Colombia, Mexico, India and Pakistan Szeidl and Szucs (2021, Table A.1 in Supplementary Material).)

[5] Szeidl and Szucs (2021) define a *favor* (advertising or news coverage) as "an allocation not driven by a conventional market force like audience preferences." (p. 282)

I use data from Turkey since, despite a series of privatizations, Turkey still has many SOEs that place commercial ads on media outlets in competition with private enterprises in the same sector. I focus on the post-2002 era by building on previous, mostly descriptive and qualitative, studies of media capture during the rule of the Justice and Development Party (AKP) (Such as Yanatma, 2021; Yeşil, 2018; Coşkun, 2020). This period serves as a compelling case study to explore whether incumbents exploit state advertising as a tool for media capture, given the AKP's history of leveraging state resources to drive the opposition voice out of the mainstream media. At the beginning of Erdoğan's rule in 2002, media ownership was highly concentrated among a few conglomerates, mainly the Doğan Group, Çukurova Group, Bilgin Group, and Uzan Group, none of which had strong affiliations with the AKP[6]. Over 16 years, the government extensively employed the state apparatus against media owners, leading to a string of ownership changes and outlet closures. Notable and widely criticized tactics include the seizure of media assets by the Savings Deposit Insurance Fund (TMSF) due to companies' debts[7], imposing a $2.5 billion tax fine in one case against Doğan Media[8], legal prosecution of journalists[9], and outlet closures due to alleged support for terrorism[10]. By mid-2018, all of the aforementioned conglomerates exited the market, replaced by new owners closely linked to the AKP and Tayyip Erdoğan, most notably the Kalyon Group, the Demirören Group, and Ethem Sancak[11]. Nevertheless, state advertising in Turkey has received comparatively little academic and media scrutiny, except in cases of advertising bans imposed on opposition outlets[12]. A notable exception focusing on the distribution of state advertising is Yanatma (2021), which contends that SOEs often prefer

[6] According to an estimate, 84% of the daily newspapers circulated in Turkey in 2002 belonged to one of these conglomerates that are also active in non-media sectors (Özsever, 2004, as cited in Yanatma (2021))

[7] E.g., the media assets of Çukurova: https://www.hurriyetdailynews.com/state-seized-media-assets-of-cukurova-conglomerate-sold-to-businessman-ethem-sancak-58344

[8] https://www.reuters.com/article/idUSTRE58D5IC/

[9] E.g., Cumhuriyet Trial: https://www.bbc.com/news/world-europe-43899489

[10] E.g., Zaman newspaper: https://www.bbc.com/news/world-europe-35739547

[11] See the reports by Media Ownership Monitoring, which document the connections of these owners with the AKP and Tayyip Erdoğan.

[12] https://stockholmcf.org/turkish-govt-imposes-record-number-of-advertising-bans-on-opposition-newspapers-in-2020/

pro-government newspapers. However, his claim is based on a descriptive analysis with limited data and anecdotes from the author's personal communications.

I exploit the last major takeover in Turkey's media industry - Demirören Holding's acquisition of the opposition Doğan Media Group in 2018[13] - to test the claim that state advertising can be instrumental in controlling media. If there is support for the claim, as argued in the literature reviewed here, we should observe that in contexts where the government wants to capture media and has the capacity to use the state apparatus against the opposition, the allocation of state advertising is politically motivated. Therefore, we expect the AKP government to follow a political strategy to maximize pro-government news coverage in the media by manipulating state advertising.

Based on theoretical studies of media capture and state advertising, we can consider two mechanisms that influence government's strategy. The government will want to channel the advertising money to outlets that are ideologically close to its position either to increase their competitiveness and financial power or to move valuable resources away from critical independent journalism. In this case, outlets with politically connected owners will receive more advertising from state institutions. Secondly, the government can use state advertising funds to directly *buy* favorable coverage from any media owner, given that all outlets value financial resources.

On the side of media outlets, owner ideology and financial incentives will determine the pro-government bias in their news coverage. Pro-government media owners can bias their coverage due to their own ideological disposition even in the absence of state advertising favors. State advertising can incentivize them to further move their news reporting strategy to a point that is more preferred by the government. Although critical outlets and journalists do not have the ideological incentive to provide pro-government bias, they can be willing to bias their coverage to receive funds from the government.

[13] According to the announcement of the Doğan Holding at the Public Disclosure Platform, assets transferred to Demirören include companies that hold the print, online and international reporting of three newspapers (Hürriyet, Posta and the sports newspaper Fanatik), TV channels (Kanal-D TV and shares of CNNTurk), a satellite TV provider (D-Smart), radios and the Doğan News Agency.

Even though an opposition media owner may be willing to sell some coverage favors from time to time to benefit from additional finances, it can be argued that politically connected outlets are more credible partners to the government who needs a continuous and reliable relationship to influence public opinion. In line with this view, Szeidl and Szucs (2021) assume in their formal model that only connected outlets can exchange favors with the government, arguing that the low trust between the government and opposition media will prevent such transactions since coverage favors and advertising favors are distributed at different times. Lower transaction costs in Besley and Prat (2006) model can also capture the idea that it is relatively easier for the government to offer transfers to connected owners.

Both ideology and exchange mechanisms suggest that we should observe a *quid pro quo* relationship between the AKP government and politically connected media owners. Therefore, after the sale of the opposition Doğan Media Group to the pro-government Demirören Group, we should expect to observe an increase in state advertising in the Doğan media outlets and a concomitant shift in their news coverage towards a pro-government position.

For my analysis, I use a sample of advertising and news coverage data from national newspapers owned by Doğan Media (Hürriyet and Posta) and a control group of eight newspapers.[14] I estimate the triple difference regression model as explained above using printed advertising space as the outcome variable. I find a positive and significant treatment effect driven by an increase in state advertising relative to private advertising after the sale relative to the pretreatment period. The same trend remained constant for control newspapers. Relative to the control newspapers, a state-owned enterprise is estimated to buy $16.04 col \times cm$ more advertising space compared to private enterprises in a week when a newspaper has a pro-government owner. The treatment effect is consistent with large advertising favors from SOEs to connected outlets, as it is approximately equal to the mean and 23% of the standard deviation of advertising space in the newspaper-advertiser-week level data.

[14] The other media assets subject to the same acquisition, such as TV channels and radios of Doğan Media Company, are not included in the analysis. Advertising data covers all banking sector ads printed in ten newspapers in the sample. Section 2.1 and Section 2.2 explain the selection of control newspapers and advertising data.

For the analysis of news coverage, I construct a measure of pro-government bias, which captures the sentiment in news articles covering the Turkish economy on a continuous negative-positive scale. I expect outlets providing coverage favors to the government to positively bias their economic news reports since a positive perception of the economy will increase the support for the government. Previous studies show that the incumbent economic rhetoric emphasizing its relative competence could persuade citizens in Turkey (Akbıyık and O'Donohue, 2025), and exposure to the incumbent rhetoric through media consumption can affect people's assessments and beliefs about the state of the Turkish economy (Yağci and Oyvat, 2020). Yağci and Oyvat (2020) find that consumers of pro-government media in Turkey are more likely to believe that the national economy would be in a worse situation if the challenger replaced the incumbent. The same study also suggests a positivity bias in their evaluations of the Turkish economy. They show that people anchor their assessments of the national economy to their assessments of personal/household finance; however, media can weaken this connection as consumers of pro-government media are more likely to think that the national economy fared better than their own households (Yağci and Oyvat, 2020).

This paper leverages a large corpus of news reports collected from the web, which contains more than 3 million news articles from ten newspapers. To select reports covering the Turkish economy, I fine-tuned a BERT model on the text classification task. Then, I construct a sentiment score for each news article using the API version of a GPT model.Using sentiment scores, I analyze the effect of politically connected owners on pro-government media bias in a synthetic difference-in-differences (SDID) design, introduced in Arkhangelsky et al. (2021). The SDID is argued to be more robust compared to the classical difference-in-differences design whenever unobserved unit- and time-varying latent factors affecting the outcome might be a concern. I find strong evidence for coverage favors from the pro-government media to the government, estimating a significant increase in sentiment scores due to the ownership change in a magnitude of one standard deviation in the sentiment scores of treatment newspapers.

Section 2 describes the data sets and variables. Section 3 analyzes the content of advertisements using a Naive Bayesian classifier and presents evidence for advertising favors in a triple-difference estimation. Section 4 explains how language models are used and identifies the effect of pro-government owners on biased news coverage. Section 5 concludes.

2 Data

2.1 Newspapers

Data include ten national newspapers in Turkey published between 2015 and 2020. Two of them are treatment newspapers which belonged to Doğan Media Company acquired by the pro-government Demirören Group in May 2018[15]. Owners of the other eight newspapers did not change over the sample period. They are selected based on their circulation rates and reader profiles to construct a relevant control group.

Table 1 shows newspapers in the data set ordered by their share in circulation in 2015. The reader profile indicates whether newspapers appeal to groups who are *conservative* (if readers predominantly support the incumbent AKP), *opposition* (if most readers support the opposition party), or *mainstream* (if readers support the incumbent and the opposition parties relatively equally) (Yıldırım et al., 2020). Owner data is collected from online publicly available resources, mainly the websites of newspapers, Public Disclosure Platform, and Media Ownership Monitor (MOM)[16]. MOM, a project undertaken by the international human rights organization Reporters Without Borders, collects information about media owners in various countries. Their reports on Turkey extensively discuss the ties of Demirören[17] and

[15]The executive board of Doğan Media approved the sale officially on April 06, 2018. The sale was publicly announced approximately two weeks before the official executive approval. The final sale date, when the Demirören Group took over the assets of the Doğan Media Company, is 16 May 2018 (Source: Public Disclosure Platform of Turkey (KAP)).

[16]https://turkey.mom-rsf.org/en/

[17]https://turkey.mom-rsf.org/en/owners/companies/detail/company/company/show/demiroeren-group/

Table 1: Newspapers in Data

Newspaper	Owner (2015-2020)	Reader Profile	2015 Circulation Share	2015 Circulation Rank
Hürriyet	Doğan Media Group	Mainstream	8.3%	2
	Demirören Group (since May 2018)	-	-	-
Posta	Doğan Media Group	Mainstream	7.7%	3
	Demirören Group (since May 2018)	-	-	-
Sözcü	Estetik Publishing	Opposition	7.4%	4
Sabah	Kalyon Group	Conservative	7.2%	5
Habertürk	Ciner Group	Opposition	4.2%	6
Türkiye	İhlas Holding	Conservative	3.5%	8
Milliyet	Demirören Group	Mainstream	3.4%	9
Takvim	Kalyon Group	Conservative	2.7%	11
Vatan	Demirören Group	Mainstream	2.3%	16
Cumhuriyet	Yeni Gün Haber Ajansı	Opposition	1.2%	19
Total			48%	

Note: Table lists the newspapers in the sample with their owners. Reader profiles in 2015 are taken from Yıldırım et al. (2020). Circulation shares and rankings for the same year are calculated using the replication data of the same study.

Kalyon[18] Groups with the government and Erdoğan himself, claiming that these business conglomerates are initially incentivized by the government to enter the media sector by acquiring popular outlets. This paper refers to Demirören, the new owner of Doğan Media, and Kalyon as pro-government owners relying on the evidence collected by MOM.

For every reader profile, *mainstream, opposition* or *conservative*, newspapers with the highest circulation rates in 2015 are included to the control group since the treatment group consists of top-selling mainstream newspapers. Based on their total circulation in 2015, the sample covers top four mainstream (two in the treatment and two in the control), top three opposition, and top three conservative newspapers after excluding the newspapers that were active in 2015 but closed before the treatment time[19], and newspapers that only cover

[18]https://turkey.mom-rsf.org/en/owners/companies/detail/company/company/show/kalyon-group/

[19]Newspapers at the rank 1, 17 and 18 (Zaman, Bugun and Meydan) were closed by a decree in July 2016 before the Doğan's sale in 2018.

Table 2: Banking Sector Advertisers in the Sample

Owner Type	Bank Type	# Inst.	Ads (2015-2020) Count	Space (colXcm)
Private	Commercial	19	7,729	1,022,186
	Investment	3	63	11,477
	Participation	2	259	43,932
	Inter-banking Org.	2	26	3,594
State-owned	Commercial	3	2,511	417,230
	Investment	1	8	436
	Participation	2	102	22,667
		32	10,698	1,521,522

Note: Table shows the distribution of banking sector institutions, their ads and total ad spaces in the sample by advertiser type. Table A.1 in the Appendix demonstrates the same by the institution name.

sports[20].

2.2 Advertising Data

Advertising data covers all banking sector ads printed in the ten newspapers between 1 January 2015 and 31 December 2020[21]. Data is provided by Interpress, a leading media monitoring company based in Turkey. It is an ad-level data containing $10,698$ observations. I have variables for newspaper name, publishing date, ad type[22], and printed space ($col \times cm$) for every ad. Additionally, two variables - *product* and *title* - describe the advertised product and record the main text on an advertisement and allow me to construct a variable for the advertiser. I identified 32 institutions in the banking sector that advertised in a newspaper in the sample at least once between 2015 and 2020[23].

The analysis is limited to the banking sector ads since it allows us to compare the advertising behavior of various private and state-owned enterprises (SOEs) competing in the domestic market and presumably having similar economic incentives as their ads promote

[20] Newspapers ranking at seven (Fotomac) and ten (Fanatik) cover only sports. Four newspapers ranked between 12 and 15 (Yeni Safak, Gunes, Aksam and Star) had conservative reader profiles in 2015.

[21] Data for Habertürk and Vatan newspapers ends on 5 July 2018 and 1 November 2018, respectively, when they stopped printing papers and continued as online outlets.

[22] Ad type is promotional ad (*tanitici reklam)* for all ads in the data set.

[23] See Table A.1 in the Appendix for a list of advertisers.

similar products[24]. 30 out of 32 banking sector institutions in data are banks listed on the website of Turkey's Banking Regulation and Supervision Agency (BRSA)[25]. BRSA groups banks into three types based on their activities in the sector: (1) deposit (commercial) banks, (2) development and investment banks and (3) participation banks. Table 2 shows that there are both private and state-owned banks of each type in my data set.

The top advertisers among both private and state-owned institutions are commercial banks, which advertised 95.7% of 10,698 ads printed in ten newspapers between 2015 and 2020. Approximately 25% of the commercial bank ads were placed by state-owned banks which compromises the 95.8% of all ads placed by state-owned banks. Participation banking is the name used for Islamic banking in Turkey. Participation banks placed less than 4% of ads in my sample and provide Islamic banking services alternatives to the commercial banks' products. Participation banks must have incentives to target conservative readers who are more likely to choose Islamic banking services.[26] On the other hand, both private and state-owned commercial banks advertise typical banking services targeting similar audiences as analyzed in Section 3.

2.3 News Data

The news data comes from the online news scraped from the websites of ten newspapers included in the analysis. It is collected from Common Crawl repositories.[27]I constructed my data set using all news reports in the ten newspapers published between in three years, 2017-2019. Raw data retrieved from Common Crawl contain the HTML source code of news reports that allow me to extract the following variables: news text, title, date published/-modified, and news section.

[24]Appendix A.2 compares the distribution of banking sector ads in my sample to the total advertising space in the newspapers using data from Yanatma (2021).

[25]www.bddk.org.tr/Kurulus/Liste/90

[26]Main participation banks operating in Turkey had been a private bank, Bank Asya (until its license was canceled in 2016), and subsidiaries of foreign banks (such as the Al Baraka Group) until two state-owned banks (Ziraat and Vakif) were approved to start their participation banking branches in February and June 2015. Source: Public Disclosure Platform (KAP) [1], [2]

[27]https://www.commoncrawl.org

For every news report, I also construct a dummy variable, *region*, indicating whether a report is about Turkey, and a categorical variable *topic* showing whether a report covers economy, sports, or other news by using a Turkish BERT-based model that I fine-tuned separately for the region and topic classifications.[28] News articles classified into *economy* and *Turkey* constitute my analysis data since I investigate the effect on news coverage regarding the Turkish economy. Table 3 shows the distribution of news reports in the analysis data by newspaper and year. Finally, I construct a measure of sentiment scores on a continuous scale $[-1, 1]$ for each news report covering Turkish economy using OpenAI's GPT-4o-mini. Section 4 explains the procedures of topic modeling and sentiment scoring with BERT and GPT as implemented in this paper.

Table 3: Labeled and Predicted News Covering Turkish Economy

Newspaper	2017	2018	2019	Sum
Cumhuriyet	939	2698	3256	6893
Habertürk	22,703	19,109	34,462	76,274
Hürriyet	55,453	33,668	28,660	117,781
Milliyet	10,767	13,654	24,161	48,582
Posta	3639	8496	6419	18,554
Sabah	26,247	19,284	18,072	63,603
Sözcü	5826	10,390	11,248	27,464
Takvim	1546	5375	18,213	25,134
Türkiye	6364	6818	10,371	23,553
Vatan	2143	3654	3246	9043
All	135,627	123,146	158,108	416,881

Note: Table shows the number of news articles that are labeled or predicted to have *Economy* and *Turkey* labels.

[28]BERT (Bidirectional Encoder Representations from Transformers) is a language representation model introduced by the Google AI team (Devlin et al., 2019). It is pre-trained on several downstream tasks including text classification. I use a BERT model pre-trained for Turkish, *dbmdz/bert-base-turkish-uncased*, by the MDZ Digital Library team (dbmdz) at the Bavarian State Library. The model is open-source and available at HuggingFace [link].

3 Analysis of Advertising

3.1 Descriptive Analysis of Advertising Space and Content

I begin my analysis with the economic incentives of state-owned and private banks for advertising. The top advertisers in my data are commercial banks that placed more than 95% of private and state ads. The visual and textual content of the ads allow us to infer which demographic groups are being targeted and what kind of products are being promoted. Figure A.4 in the appendix shows two examples for ads printed on the newspaper Hürriyet in Dec 19, 2017. The first one is an ad by the state-owned Vakifbank, which features a family with a child and has a title that translates as 'We are with you to meet all your needs with the New Year loan.'[29]. The text below the title suggests that they provide low-interest loans and easy repayment options. The second one is a Garanti Bank advertisement that promotes loans for small and medium-sized businesses. Its title targets small business owners with a commercial loan option, and the text below the title promises a three-month grace period before the first installment.

Examples suggest that private and state bank ads share similar market-based motivations for advertising. To corroborate this argument, I conduct a systematic analysis of the title texts in the ads using a Multinomial Naive Bayesian classifier. I find that state-owned and private banks do not differ substantively in terms of vocabulary they have chosen and services they have promoted, suggesting a shared economic motivation for advertising in newspapers.

First, I construct a document-term matrix[30] of titles using unigrams and bigrams. I remove bank names from titles and follow a standard procedure of text normalization which involves stemming, converting to lowercase and dropping stop words[31]. Then, I fit a Multinomial Naive Bayes classifier where the classes are *stateowned* and *private*. The details of the

[29]The original text is "Yeni Yil Kredisi'yle Tum Ihtiyaclarin Icin Yanindayiz".

[30]Application with TF-IDF (term frequency − inverse document frequency) returns similar results. A term in the matrix is a normalized word (unigram) or a normalized two-word combination (bigram).

[31]Turkish stopwords are downloaded from github.com/Alir3z4/python-stop-words. For stemming, I use a Turkish NLP package called *Zemberek* available at github.com/Loodos/zemberek-python.

model and its application are in Appendix A.3. I retrieve the likelihood of terms conditional on class, which can be interpreted as "a measure of how much evidence" a term contributes that a class is the correct one[32].

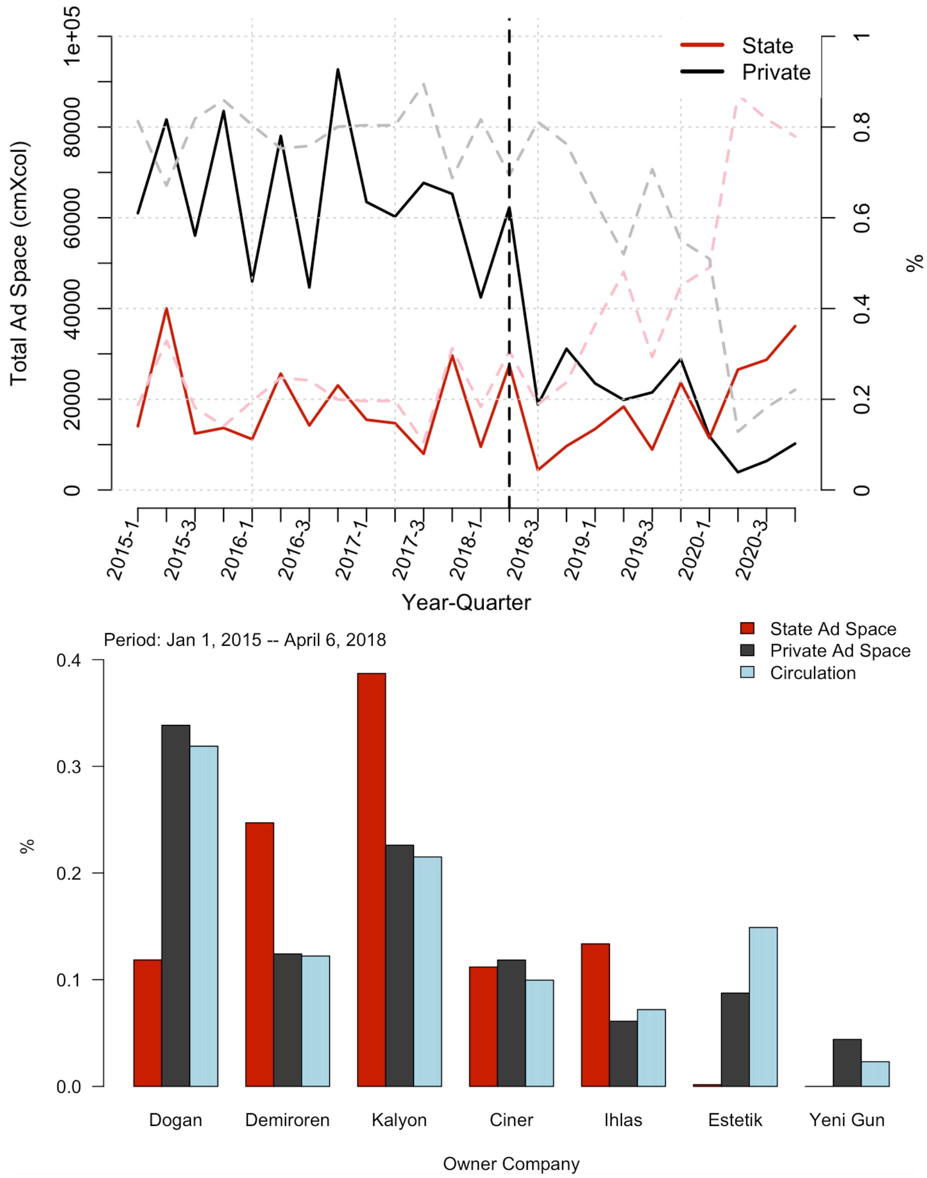
Table A.6 in the appendix lists 25 terms having the highest probabilities conditional on each class. Ten out of 25 terms are common to both classes which include words such as loan (*kredi*), SME (*kobi*), holiday (*bayram*), and need (*ihtiyac*). Among the top 10 terms for *stateowned*, only three of them are not shared with *private*. Two of those terms are the proper names of credit cards offered by some state-owned banks.

In general, words with the highest likelihood given any class can be associated with economic incentives of a typical deposit bank. A group of them targets particular customer bases such as small business owners (*esnaf*), farmers (*ciftci*) and pensioners (*emekli*). Another group of words are related to the services banks typically offer, which are card (*kart*), investment (*yatırım*), loan (*kredi*), account *(hesap)*, fund (*fon*), interest (*faiz*) and mobile (*mobil*). Finally, there is a group of words that can be used to attract customers to prefer their services, such as want (*iste*), new (*yeni*), support (*destek*), make grow (*büyüt*), more (*fazla*), gain (*kazan*), and opportunity (*fırsat*).

While placing similar ads, state-owned and private banks had different advertising trends. The top panel of Figure 1 shows the quarterly aggregated time trends of total advertising space printed in ten newspapers. The Doğan Media's sale corresponds to the second quarter of 2018. We observe that the ratio of state advertising space to private advertising space fluctuated around 0.25 between the first quarter of 2015 and the third quarter of 2018. Then, the ratio increased drastically as the private banks kept decreasing their newspaper advertising and the state-owned banks followed an opposite strategy. By the end of 2020, we see that the previous ratio is simply reversed, being approximately at 4. Figure A.1 in Appendix plots the same with the number of ads instead of printed ad space, and displays a similar trend.

[32]nlp.stanford.edu/IR-book/html/htmledition/naive-bayes-text-classification-1.html

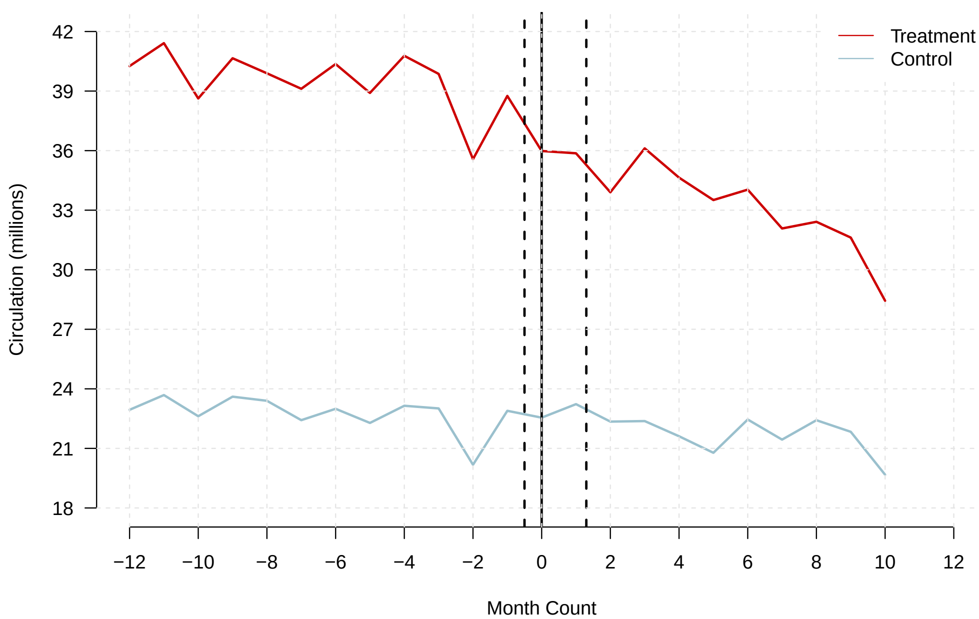
Figure 1: Quarterly Trend and Pre-treatment Distribution of Printed Advertising Space



Note: Top panel shows the contrast between trends in state and private advertising. Solid lines draw the total ad space bought by state-owned (red) and private (black) banks in ten newspapers in the quarters. Dashed lines show the shares in total ad space with values indicated at the y-axis at the right. The vertical dashed line at 2018-02 indicates the quarter that contains the sale day (April 6, 2018). The bar chart at the bottom panel shows the shares of newspaper owning companies in state and private advertising and circulation during the pre-treatment period. Percentages are calculated within the sample of ten newspapers. Table 1 lists newspapers in the sample together with their owner companies. Demirören and Kalyon are media owners with known political affiliations with the incumbent, while outlets owned by Doğan, Estetik, and Yeni Gün are recognized for their dissenting editorial perspectives.

The bottom panel shows the distribution of total advertising space in the pre-treatment period over the newspapers by their owner companies, and compares the advertising shares to the circulation shares calculated within the sample. We see that two newspapers owned by Doğan Media accounted for 32 percent of the total sales of ten newspapers in the sample during the pre-treatment period, and received 34 percent of private banking ads in the sample. Conversely, their share in the state advertising remained around 12 percent. For all owner companies, shares in private ad space closely follow their shares in circulation. However, state banks appear to have a strong preference for newspapers of Demirören and Kalyon Groups, two conglomerates that entered the media market during the AKP governments. They also placed disproportionately less advertising on two newspapers (Sözcü and Cumhuriyet) owned by Estetik Publishing and Yeni Gun News Agency, which hold a strong opposition line.

Figure 2: Monthly Trend in Circulation



Note: Figure shows the parallel trends in circulation of treatment and control newspapers before the sale, and the negative effect of sale on the circulation of treatment papers. The solid line marks the cut-off day when the sale was officially approved by the executive board of the Doğan Media. The dashed lines show the day that the sale was publicly announced and the day that the sale was finalized. Table A.2 shows the regression results. I estimate a 5.1 million decline in the average circulation of Hürriyet and Posta due to the sale relative to the control newspapers.

Figure 2 tracks the average number of copies of treatment versus control newspapers sold per month a year before and after the sale. It shows a steeper decline in the circulation of treatment newspapers after the sale relative to the control group and relative to the pre-treatment period. Appendix Table A.2 regresses the circulation on treatment controlling for newspaper and time fixed effects. The results show that the acquisition of the Doğan Media by Demirören is associated with a 5.1 million decline in the average monthly circulation of Hürriyet and Posta relative to the control newspapers.

3.2 Causal Effect of Political Incentives on State Advertising

Building on the triple differences framework developed in Olden and Møen (2022) and further refined by Strezhnev (2023), I estimate the effect of political incentives on the distribution of state advertising in newspapers. The baseline specification (Equation 1) regresses the advertising space on a full set of interactions between three dimensions: whether the advertiser is state-owned ($StateOwned$), whether the observation is after the Doğan Media sale ($Sale$), and whether the newspaper is one in which political influence is presumed to operate after the sale ($TreatmentPaper$).

$$\begin{aligned} AdSpace_{nat} = {} & \beta_1(StateOwned_{at} \times Sale_t \times TreatmentPaper_n) + \beta_2(Sale_t \times TreatmentPaper_n) + \\ & \beta_3(StateOwned_{at} \times Sale_t) + \beta_4(StateOwned_{at} \times TreatmentPaper_n) + \\ & \beta_5 StateOwned_{at} + \beta_6 Sale_t + \beta_7 TreatmentPaper_n + \phi_t + \psi_n + \gamma_a + \epsilon_{nat} \end{aligned} \quad (1)$$

$AdSpace_{nat}$ is total space of ads by advertiser a in newspaper n at time t, measured with $cm \times column$. $TreatmentPaper_n$ is a dummy variable equal to 1 if $n \in \{Hurriyet, Posta\}$; otherwise 0. $Sale_t = 1$ if $t \geq 06April2018$, the day that the executive board of the Doğan Media Company officially approved the sale[33]. Both treatment newspapers are transfered

[33]The sale was publicly announced approximately two weeks before the official executive approval. The final sale date when the Demirören Group took over the assets of the Doğan Media Company is 16 May 2018.

at the same time. $StateOwned_{at} = 1$ if an advertiser is state-owned at t; 0 if private. The specification allows for a variation in a bank's ownership over time, while none of the banks in the sample was privatized or nationalized during 2015-2020. Time t can indicate days, weeks, or months[34]. I cluster standard errors by newspaper and use a 2-year bandwidth for the main estimations. Since cluster-robust standard errors tend to over-reject the null with only 10 clustering units, I use the Wild Cluster Bootstrap (WCB) with the Webb weights to calculate p-values (MacKinnon and Webb, 2018; Webb, 2023) and report both cluster-robust standard errors and WCB p-values. I use the restricted wild bootstrap imposing the null hypothesis as implemented by Roodman et al. (2019)[35].

The identification strategy relies on the assumption that private advertisers do not have the political motivation the government has. On the other hand, as shown in the previous section, state and private advertisers in the analysis data have the same economic incentives to advertise. The 2018 acquisition by a pro-government conglomerate can change the economic motivations as to why an enterprise might want to advertise in the Hürriyet and Posta newspapers through an impact on their reader profiles. A change in reader profiles must affect both private and state-owned banks' advertising since they must be targeting the same audience. On the other hand, the change in the political connections of newspapers will affect the preferences of only state-owned banks, since private banks do not distribute advertising favors.[36] Therefore, the causal parameter, β_1, estimates the effect of political incentives on state advertising, provided that the differences in the pre-sale outlet choices of

[34]Weeks and months are constructed as 7-day and 30-day periods around the sale day and might not correspond to calendar weeks and months.

[35]The default algorithm in *fwildclusterboot:boottest* is used except with *type="webb"* and *B=9999* in R.

[36]This assumption simplifies the case since, in reality, the government can exert coercive or non-coercive influence over the private advertisers as well. If this is the case, the government's influence will reduce the difference between state advertising and private advertising. Hence, the estimate of the causal parameter will be biased towards zero. Then, the actual effect size will be at least as large as my point estimate.

state-owned and private enterprises are parallel. Formally, the causal parameter is

$$\beta_1 = [E(AdSpace|T, StateOwned) - E(AdSpace|T, Private)] - \\ [E(AdSpace|C, StateOwned) - E(AdSpace|C, Priv)] \quad (2)$$

which can be arranged as the difference between the treatment effect on state advertising estimated with a DD model and that on private advertising,

$$\beta_1 = [E(AdSpace|T, StateOwned) - E(AdSpace|C, StateOwned)] - \\ [E(AdSpace|T, Private) - E(AdSpace|C, Private)] \quad (3)$$

where T and C stand for treatment and control. Hence, the causal parameter of our interest estimates the differential effect of the treatment on the state and private advertising, which, I argue, is due to the political incentives.

Table 4 reports the results using weekly aggregated data. I report cluster-robust standard errors in parenthesis and WCB p-values calculated with the Webb weights in brackets. As expected, WCB estimations are more conservative and fail to reject the null more frequently compared to cluster-robust standard errors. In the baseline model (Model 1) and the model controlling for circulation (Model 2), I find strong evidence for positive and significant treatment effect as the WCB p-value for the coefficient of the triple interaction term is less than 0.05. Models 3 and 4 reflect low power to estimate β_1 with the WCB p-values (0.058 and 0.083) failing to reach the 5% significance. As argued in MacKinnon and Webb (2018), under-rejection can be an issue with the null-imposed restricted wild bootstrap when there are only two treated clusters.

Model 1 and 2 suggest that state-owned advertisers relative to the private advertisers respond to the political realignment induced by the sale by increasing their ad space in treatment newspapers. The treatment newspapers receive an additional $16cm \times column$

Table 4: Baseline Results for Advertising Favors Accounting for Circulation

Dependent variable:	$AdSpace$ 1	$AdSpace$ 2	$AdSpace \times Circulation$ 3	$\frac{AdSpace}{Circulation}$ 4
$Circulation$		1.412		
		(0.95)		
		[0.159]		
$StateOwned$	−66.981	−68.093	−481.828	−12.914
	(14.29)	(14.40)	(159.63)	(2.01)
	[0.001]	[0.000]	[0.002]	[0.001]
$Sale$	−9.843	−4.459	−39.622	−0.627
	(3.43)	(3.00)	(20.59)	(0.69)
	[0.007]	[0.186]	[0.062]	[0.384]
$TreatmentPaper$	74.948	64.467	563.852	12.754
	(12.60)	(17.76)	(128.99)	(1.77)
	[0.00]	[0.02]	[0.00]	[0.00]
$StateOwned \times Sale$	3.292	3.40	29.145	0.38
	(2.64)	(2.80)	(22.06)	(0.44)
	[0.245]	[0.264]	[0.205]	[0.387]
$StateOwned \times TreatmentPaper$	−18.904	−18.904	−138.709	−2.711
	(5.55)	(5.55)	(28.12)	(1.54)
	[0.135]	[0.140]	[0.080]	[0.186]
$Sale \times TreatmentPaper$	−6.621	−4.996	−94.404	−0.106
	(2.04)	(2.12)	(28.15)	(0.25)
	[0.110]	[0.087]	[0.083]	[0.689]
$StateOwned \times Sale \times TreatmentPaper$	16.038	16.419	141.829	1.977
	(2.64)	(2.80)	(27.42)	(0.49)
	[0.044]	[0.046]	[0.058]	[0.083]
Num. obs.	31584	30784	30784	30784
$E(Outcome_{nat})$	16.413	16.413	130.849	3.138
$S(Outcome_{nat})$	70.782	70.782	577.273	15.869
Time	Week	Week	Week	Week
Bandwidth (Sale week = 0)	−52 : 52	−52 : 52	−52 : 52	−52 : 52
Fixed Effects (ϕ_t, γ_a, ψ_n)	Yes	Yes	Yes	Yes
Clustered SE (Newspaper)	Yes	Yes	Yes	Yes
Num. groups: Newspaper	10	10	10	10
Num. groups: Advertiser	32	32	32	32
Num. groups: Time	105	102	102	102
R^2 (full model)	0.132	0.133	0.139	0.078
Adj. R^2 (full model)	0.128	0.129	0.135	0.074

Note: Table shows the baseline regression results with the triple difference model and alternative specifications accounting for circulation. Models are estimated with data at week-newspaper-advertiser level. Standard errors (in parenthesis) are clustered by newspaper. P-values (in brackets) are calculated using the Wild Cluster Bootstrap (WCB) with the Webb weights since the number of clusters is ten with two being treated. Treatment effect remains significant at the 5% level even with the conservative WCB estimates in the baseline specification (Model 1) and after controlling for circulation (Model 2).

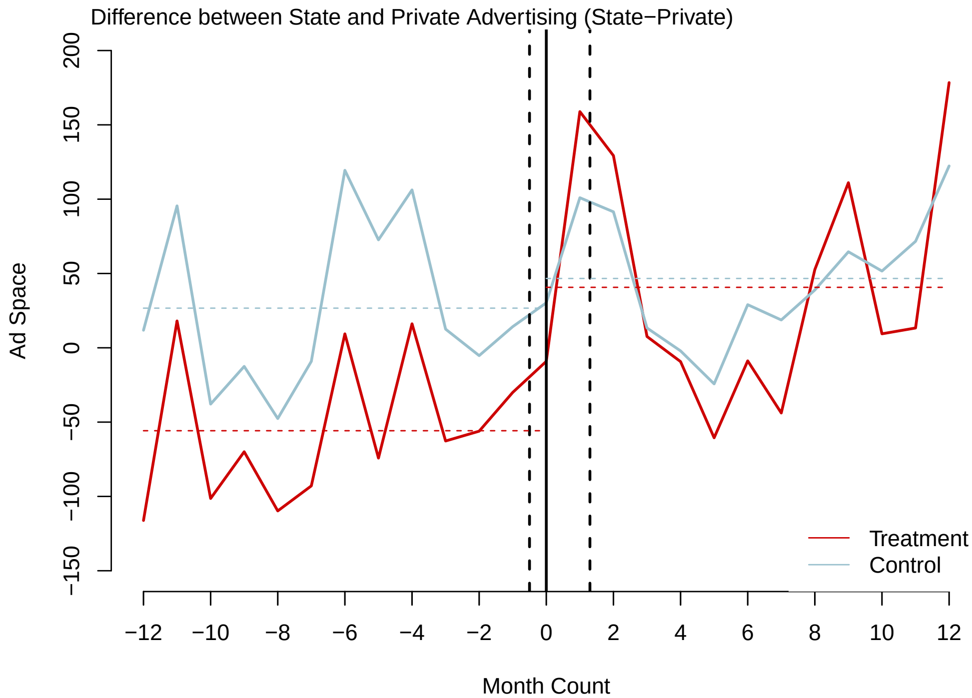
ad space weekly from state-owned banks due to their political connections, which can be interpreted as the size of advertising favors. Given that the weekly average of ad space by an advertiser in a newspaper is $16.41cm \times column$ in my sample, the treatment effect implies a substantial volume of advertising favors.

Table A.3 in the Appendix shows the robustness of Model 1 to the placebo specifications estimated with a two-year bandwidth around the placebo sale dates by shifting the actual sale date by 52 weeks. I estimate four regressions with placebo sales in weeks 52 and 104 before and after the actual sale week. The coefficient of the triple interaction term is not significant in any of these placebo regressions, even under the more liberal cluster-robust inference susceptible to over-reject the null with ten clustering units. This proves that the treatment effect estimated with Model 1 is not driven by a serial autocorrelation in the ad space.

Figure 3 draws the raw monthly aggregated group averages, $[E(AdSpace|T, StateOwned) - E(AdSpace|T, Private)]$ and $[E(AdSpace|C, StateOwned) - E(AdSpace|C, Private)]$, showing the pre- and post-sale trends in the difference between state and private advertising. The figure shows a large pre-treatment difference between the two lines in every month until the sale, which is estimated to be -82.46 on average corresponding to the coefficient of $StateOwned \times TreatmentPaper$ in the month-level regression results (Appendix Table A.4). The gap closes almost entirely in the post-treatment period due to a large jump in the treatment difference. The visual inspection of the Figure 3 demonstrates that there is not a visible divergence or convergence between the treatment and control differences in the pre-treatment period. Appendix Figure A.3 reports event study plots with fully interacted month dummies and fixed effects normalized to the pre-treatment average[37]. The event study plot for the triple difference coefficients (upper panel) shows no systematic trend before the

[37] I avoid using $month = -1$ as a single reference month due to high month-to-month variance in ad space and a potential anticipation problem since the sale was publicly announced two weeks before the official executive approval. Averaging across the pre-treatment period reduces the effect of potential short-term anticipation. Note that normalization to the average instead of $month = -1$ only shifts every coefficient by a common constant and leaves the shape of the path unchanged.

Figure 3: Trends in the Triple Difference Model



Note: The figure shows the trend of the difference between state and private advertising in treatment (red) and control (blue) newspapers for 12 months before and after the sale. Mathematically, the red line draws $E(AdSpace|Treatment, StateOwned) - E(AdSpace|Treatment, Private)$, and the blue line draws $E(AdSpace|Control, StateOwned) - E(AdSpace|Control, Private)$. The solid line marks the cut-off day when the sale was officially approved by the executive board of the Doğan Media. The dashed lines indicate the public announcement of the sale and the final takeover by Demirören. Horizontal dashed lines mark the average value of the difference in ad space for the treatment and control groups in the pre- and post-treatment periods. Figure A.2 in the Appendix demonstrates the trends decomposed into two DD estimations with raw group averages. Figure A.3 shows the coefficients of interactions with month dummies accounting for fixed effects.

sale. Every post-treatment coefficient is positive while some are not significant. Decomposing the estimate into its $treatment - control$ differences for state and private advertising components shows that the two differences track each other closely before the sale and begin to diverge systematically afterwards.

Model 3 uses an alternative outcome variable defined as the product of ad space and circulation, $AdSpace_{nat} \times Circulation_{nt}$. Newspaper circulation can be considered as a measure of value to the advertiser for a unit ad space in the newspaper since it measures the ads' impressions (the reach to the audience). It must also be correlated with the price of a unit ad space for which I do not have data. Consistent with the results from Model 1 and Model 2, the point estimate is large, at 108.4 percent of the outcome mean and 24.6 percent of its standard deviation, though imprecisely estimated ($WCBp = 0.058$).

Model 4 estimates the same model with the outcome variable normalized by circulation, $\frac{AdSpace}{Circulation}$. It is a measure of how much advertising is delivered per audience, constructed to capture the variation in *AdSpace* net of its impressions value. The triple-difference estimate is positive but imprecise. The decomposition, however, appears to be informative and describes the mechanism. In the placebo DD, private advertising in treatment and control newspapers overlaps across the full two-year window with no visible response to the sale (bottom right panel of Figure A.2). Once ad space is expressed per reader, the decline in private advertising documented with *AdSpace* is accounted for by the fall in circulation. The primary DD shows no such pattern (bottom middle panel). State advertising per reader rises in the treatment newspapers after the sale and the pre-existing gap closes. Private advertisers thus behaved as audience-driven buyers throughout, while state-owned advertisers increased their purchases in newspapers that were losing readers.

4 Analysis of News Coverage

4.1 Topic Modeling with BERT

I trained two models based on the Turkish BERT model (*bert-base-turkish-uncased*) for the supervised text classification task to predict the topic and region covered in news. I parsed the website sections under which the news articles were published to generate topic and region labels instead of relying on human-coders. Then, I manually grouped the web news sections into standardized labels to reduce the number of categories. For example, sections such as trade, housing, and consumers are grouped into "Economy" label. Sections such as world, Europe, US are grouped into "Not Turkey". There are a substantial number of news articles published under sections, such as breaking news, current news or homepage,

Table 5: Sample Size of Data Sets Used to Train BERT Models

Topic Model		**Region Model**	
Economy	215,324	Turkey	432,018
Sports	378,109	Not Turkey	180,634
Other	528,552		
No label	1,932,391	No label	2,441,724

Note: Table shows the number of news articles with each label. Labeled data is randomly split into training (80%), validation (10%), and test (10%) sets. Fine-tuned models are used to predict a label for news with no label.

which do not indicate any region or topic. Another group of news URLs returned NA article sections when parsing their HTML code. They constitute my unlabeled or prediction data.

For the topic model, I reduced the number of labels to three, *Economy*, *Sports*, and *Other*, where the main label of interest is *Economy*. *Other* category combines news from topics such as politics, education, entertainment, and health. Table 5 shows the number of articles with each topic label. For the purpose of classification, I assume that topics are mutually exclusive and the model is trained to return a probability distribution over the labels and pick the label with the highest probability. The second task is a regression type model, which predicts the probability of *Turkey*. Right panel of Table 5 shows how many news articles are labeled as *Turkey* and *Not Turkey*.

The following procedure is followed separately for two models. First, I randomly select 80% of the labeled data for training, 10% for the validation, and the remaining 10% for the test. I use a batch size of 8 and fine-tuned for 5 epochs over the training data for the text classification task. Checkpoints are saved after each epoch, and the model that yields the lowest loss with the validation data is selected[38]. Finally, the model performance metrics are calculated with the test data.

Table A.10 in the Appendix shows the performance metrics of both models. The accuracy, precision, recall, and F1 scores for all categories are greater than 94% with both validation

[38]The models are fine-tuned using two cores of NVIDIA Tesla V100S-PCIE-32GB and 52 cores of CPU in a Slurm cluster.

and test sets, as can be expected from a transformer-based model fine-tuned on large data.

4.2 Sentiment Scoring with GPT

I use the API version of OpenAI's GPT-4o-mini-2024-07-18 to measure the sentiment in news articles reporting on the Turkish economy. I divide articles into *chunks* of at least 40 words, provided that chunks do not break sentences[39] since single sentences can be too short to retain any context or sentiment. The procedure returned over 2.7 million chunks. Large language models (LLM) are widely acknowledged as highly accurate models that outperform various other classifiers (Le Mens and Gallego, 2025; Törnberg, 2024). Since I have a large data set to classify and no labeled sentiment data[40] to fine-tune an LLM, or apply a supervised method, I use zero-shot prompting with OpenAI's chat completion method, configuring the arguments to run the model as deterministically as possible to receive stable results[41]. I use the following prompt[42] to score each chunk of news articles individually and independently.

```
f```Text: {Chunk Text}. This text is taken from a Turkish news article.
 How does this text report the state of Turkish economy?
 Pick one of the categories:
         i) `positive', if it provides a positive evaluation or a positive
            fact about Turkish economy;
         ii) `negative', if it provides a negative evaluation or a negative
             fact about Turkish economy;
         iii) `neutral', if it provides a neutral evaluation, or a neutral
            fact about Turkish economy;
         iv) `NA', if it is about another country or not informative.
```

[39] I use a Turkish NLP package called *VNLP* (vnlp.io) to get sentences.

[40] To my knowledge, there is not any publicly available human-coded data to conduct a sentiment analysis with Turkish economic news.

[41] I set the temperature argument to zero and specify a seed. Additionally, I save the system fingerprint response parameter for every completion to be able to monitor changes in the backend. Although determinism is not guaranteed, this configuration significantly reduces the variation in GPT responses, and repeated runs with the same prompt, text, and parameter values return mostly identical responses at every time even for the five-word explanation for which the prompt does not provide any wording instructions.

[42] I also tried a prompt with more detailed definitions of sentiment categories in relation to the economic news coverage. It did not change the results in a meaningful way. Concealing from the model the fact that text is from a news report did not affect the results as well.

```
Then, explain your reasoning in 5 words. Your answer should be in the
    following format:
Category: Category, Explanation: YourExplanation.
'''
```

The prompt is designed to capture the sentiment in both factual statements and evaluations. It also aims to exclude parts of a news report that mentions foreign economies[43]. Appendix B shows example GPT responses indicating that the GPT model captures the key points in news reports and correctly evaluates the sentiment.

Averaging the chunk scores, I construct a continuous article sentiment score between -1 and 1. For news article, a,

$$Sentiment_a = \frac{\#Positive_a - \#Negative_a}{\#Positive_a + \#Negative_a + \#Neutral_a}$$

4.3 Pro-Government Coverage of Economic News

The variable constructed to operationalize the concept of pro-government bias in newspapers is the sentiment score computed for each news article covering the state of the Turkish economy. Sentiment scores measure the position of news reports on a continuous scale, $[-1, 1]$, where -1 is the most negative and 1 is the most positive coverage. Prat and Strömberg (2013) and Gentzkow et al. (2015) discuss that media outlets can provide bias in different forms by filtering or framing facts. Similarly, the GPT prompt I used to construct the scores aims to capture the positivity/negativity of both factual coverage and evaluations in news reports[44]. Although factual coverage is presumably unbiased, newspapers can selectively report facts by filtering out those that are not favorable to some groups for whom they want to provide media bias. In our case, assuming that the government prefers a positive cover-

[43]Although the BERT models presented in the previous section accurately select news reports about the Turkish economy, they are trained at the article level. On the other hand, the prompt is called for each chunk.

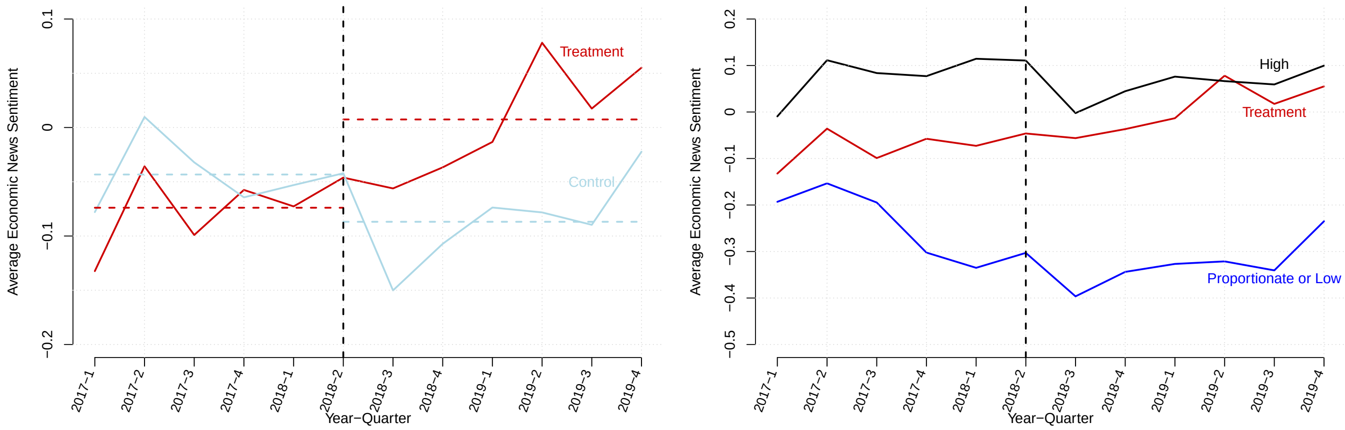
[44]The prompt (shared in Section 4.2) instructs the GPT model to select a sentiment category based on a fact or evaluation.

age of national economic conditions, newspapers providing pro-government bias will report positive facts regarding the Turkish economy more frequently. Alternatively, they can frame or evaluate facts from a more favorable/positive perspective. In the Appendix, I show examples from pro-government and independent outlets of selection and framing in news coverage about inflation (Section B.5.2) and the economic impact of the 2017 referendum (Section B.5.1). The example coverage of the 2017 referendum from the pro-government newspaper also shows the salience of economic issues for the referendum as the government argues that their preferred outcome will facilitate economic growth during the campaign period.

Sentiment scores measure the position of a newspaper relative to other newspapers. In this framework, the unbiased sentiment score for a given time period is a latent unknown variable that depends on the underlying economic conditions. For example, observing a zero sentiment in Newspaper A and a positive sentiment in Newspaper B for the same time period does not necessarily indicate newspaper B is positively biased. Newspaper B can be closer to the unbiased sentiment if Newspaper A omits to report positive news. However, the trend in the sentiment scores of Newspaper B relative to that of Newspaper A captures how their reporting strategies change over time, since the latent unbiased sentiment of the news is common to both.

Figure 4 plots the average economic news sentiment scores in every quarter between 2017 and 2019. The sale of the Doğan Media is in the second quarter of 2018. The left panel aggregates the sentiment scores by treatment status. The right panel decomposes the control group by the share of their owner companies in state advertising as presented in the bottom panel of Figure 1. *High* includes newspapers owned by Demirören, Kalyon, and Ihlas, which received disproportionately high state advertising relative to their circulations. *Proportionate or Low* averages over newspapers owned by Ciner, Estetik, and Yeni Gun, which were not favored by the government in the allocation of state advertising. The share of Ciner's newspaper in state advertising is close to its share in private advertising and circulation, whereas newspapers owned by Estetik and Yeni Gun received almost no ads from

Figure 4: Quarterly Trend in Sentiment Score by Treatment Status and Owner Companies' Share in State Advertising



Note: Figure shows the average sentiment score in newspapers in quarters by treatment status (left) by their owners' share in state advertising (right). Dashed line at 2018-02 indicates the quarter that contains the sale day (April 6, 2018). The right panel aggregates control newspapers by their owner companies' share in the state advertising shown at the bottom panel of Figure 1. *High* includes newspapers owned by Demirören, Kalyon, and Ihlas, which received disproportionately high shares in state advertising relative to their circulations. *Proportionate or Low* averages over newspapers owned by Ciner, Estetik and Yeni Gun whose share in state advertising is low or about the rate with their circulations. Figure A.5 plots the same by the owner companies instead of their shares in state advertising.

the state-owned banks. The trends in the sentiment scores are consistent with our theoretical expectations as the newspapers in the *high* group provides a more positive coverage of the Turkish economy by a large margin in every quarter.

During the pre-treatment period, the average sentiment in the control newspapers is higher compared to the treatment newspapers, while the gap narrows in the three quarters preceding the sale due to a sharp decline in the sentiment in newspapers which received proportionate or low state advertising. After the sale, we observe that the average sentiment in the treatment newspapers positively diverges from the control group as it begins to converge to the newspapers selling more ad space to the state-owned banks.

For causal estimation of the effect of political connections with the government on news coverage, I use the synthetic difference-in-differences (SDID) estimator (Equation 4) introduced in Arkhangelsky et al. (2021), and compare the results to the classical difference-in-differences (DID) estimates (Equation 5). The SDID is a weighted DID model as shown in the estimating equations:

$$(\hat{\tau}^{sdid}, \hat{\mu}, \hat{\psi}, \hat{\phi}) = argmin\{\sum_{n=1}^{N}\sum_{t=1}^{T}(Sentiment_{nt} - \mu - \psi_n - \phi_t - W_{nt}\tau)^2 \hat{\omega}_n^{sdid}\hat{\lambda}_t^{sdid}\} \tag{4}$$

$$(\hat{\tau}^{did}, \hat{\mu}, \hat{\psi}, \hat{\phi}) = argmin\{\sum_{n=1}^{N}\sum_{t=1}^{T}(Sentiment_{nt} - \mu - \psi_n - \phi_t - W_{nt}\tau)^2\} \tag{5}$$

$Sentiment_{nt}$ is the sentiment score of the newspaper n at time t, calculated as the average score of the news reports in the newspaper for the period. W_{nt} is block treatment assignment equal to 1 when $n \in \{Hrriyet, Posta\}, t > 6April2018$, the sale date. ψ_n and ϕ_t are newspaper and time fixed effects. τ is the average treatment effect. ω_n terms are newspaper weights estimated for each control newspaper. Furthermore, a common intercept weight, ω_0 is estimated together with ω_n, allowing a constant difference between the control and treatment trends after reweighting, as it is sufficient to have parallel trends for the SDID estimation. δ_t are time weights estimated for each week. For the estimation of the SDID model, first, I compute ω_n and δ_t following Arkhangelsky et al. (2021). Then, I fit the DID model with the sample weights, $\hat{\omega}_n^{sdid}\hat{\lambda}_t^{sdid}$, to estimate $\hat{\tau}^{sdid}$.

There are several reasons that SDID might be a better model in our case. SDID method, as introduced in Arkhangelsky et al. (2021), reweights and matches pre-sale trends in treatment and control groups so that the weighted data exhibit parallel trends. Time weights are designed to balance pre-sale and post-sale periods for the control units. Arkhangelsky et al. (2021) show in a placebo study that the SDID method balances the unobserved unit- and time-varying latent factors affecting the outcome, which can reduce the bias and increase precision compared to having only unit and time fixed effects in the model. Therefore, the method also addresses the issue of non-random treatment assignment, which can be a concern for our case given the importance of the Doğan Media as the largest company in Turkey's media industry at the time, and the fact that the company had been targeted by Erdoğan long before the acquisition.

Table 6: SDID and DID Results for Coverage Favors

Outcome: $Sentiment_{nt}$ (4-week Moving Averages)				
Method:	SDID	DID	SDID	DID
Treatment	0.097^{**}	0.119^{**}	0.140	0.126^{**}
	(0.011)	(0.031)	(0.070)	(0.030)
Num. obs.	960	1540	960	1540
Num. groups: Week	96	154	96	154
Num. groups: Newspaper	10	10	10	10
Controls	No	No	Yes	Yes
Fixed Effects (ϕ_t, ψ_n)	Yes	Yes	Yes	Yes
Clustered SE (Newspaper)	Yes	Yes	Yes	Yes
R^2 (full model)	0.812	0.858	0.752	0.861
Adj. R^2 (full model)	0.789	0.841	0.721	0.844

$^{**}p < 0.01$; $^{*}p < 0.05$

Note: Table shows regression results with Equation 4 and Equation 5 using data at the week-newspaper level, where the outcome is 4-week moving average of sentiment scores. Model 3 and 4 control for newspaper-week level controls: number of news reports and average number of words.

Table 6 shows the regression results with Equation 4 and Equation 5 using data at week-newspaper level, where the outcome is 4-week moving average of sentiment scores. In all specifications, I use 63 weeks before and 90 weeks after the treatment. Some weeks are dropped from the SDID estimations due to zero weights. Treatment effects in the Column 3 and 4 are estimated by accounting for two newspaper-week level covariates, the number of news reports and average number of words in news reports[45].

With all specifications, I estimate a positive treatment effect, which is consistent with the coverage favors argument[46]. The effect size can be interpreted as the magnitude of the pro-government shift in news coverage due to the political realignment of an outlet's owner relative to the general trend of news coverage in the control outlets not exposed to a change in owner connections.

Column 1 of Table 6 shows the results with the synthetic difference in differences (SDID) model. I estimate a statistically significant increase with a magnitude of 0.097 in the average

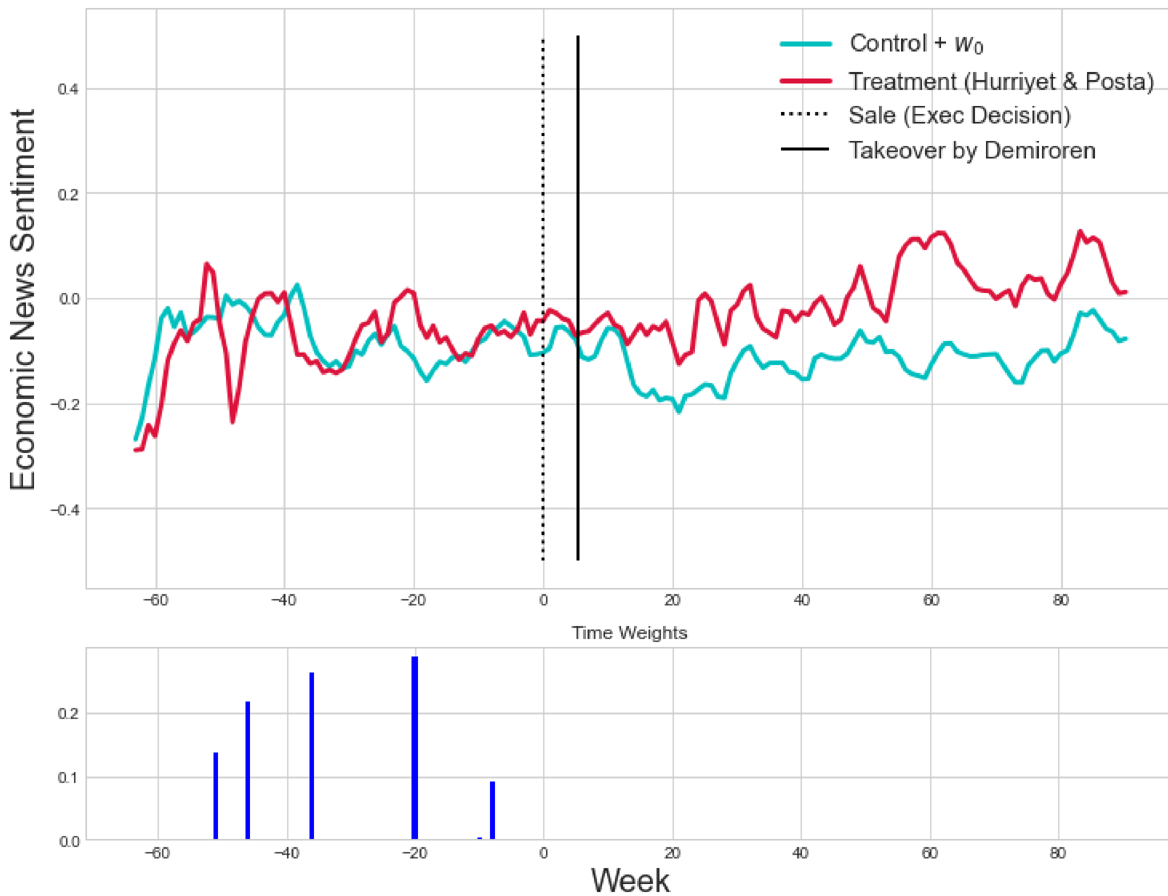
[45] In Model 3, the SDID weights are calculated after residualizing the outcome as suggested by Arkhangelsky et al. (2021).

[46] Model 3 fails to reach statistical significance because of low degrees of freedom due to having only 10 newspapers.

weekly sentiment of economic news in the treatment newspapers. Given the standard deviation in treatment newspapers' sentiment, $S(Sentiment|Treatment) = 0.093$ (Table A.9 in the Appendix), the ownership change leads to approximately one standard deviation change in the sentiment scores of treatment newspapers. The effect is 40% of the standard deviation in all data, $S(Sentiment)$. Figure 5 visualizes the model estimated in Column 1 with the time weights (λ_t^{sdid}) in the bottom panel. The green line is the weighted average of control newspapers using the estimated ω_n^{sdid} terms. The intercept estimate, ω_0, is added to overlay the treatment and control curves. The figure shows the positive effect of the treatment being more pronounced after a few weeks from the takeover by Demirören.

Column 2 shows that the DID estimate of the treatment effect is equivalent to the SDID coefficient in terms of sign and statistical significance. We find consistent results after adding covariates to the model (Column 3 and 4). Additional analysis in the Appendix Table establishes that the results are not driven by any single control unit by itself (Table A.8), and using aggregated sentiment scores instead of moving averages at day-, week- or month-newspaper level does not change the results (Table A.7).

Figure 5: Synthetic Difference-in-Differences Estimate for the Sale



Note: Figure shows trends in sentiment score over weeks for treatment and the weighted average of control newspapers. Time weights are shown at the bottom panels. The figure overlays the treatment and control curves by adding the intercept estimate ($\omega_0 = -0.066$). Vertical lines indicate the weeks that the sale was approved by the Doğan's executives (6 April 2018), and Demirören took over Doğan Media (16 May 2018). Column 1 in Table 6 presents the corresponding regression results.

5 Conclusion

This paper investigates reciprocal favors between the government and politically connected media owners, through state advertising and media bias in Turkey. Offering a rigorous quantitative analysis of how ostensibly legal economic exchanges can serve as instruments of political manipulation, the study contributes to the broader literature on media capture strategies.

The empirical analysis robustly shows that state advertising allocations systematically diverge from private advertising in a way contrary to traditional economic incentives, underscoring their instrumental role in covertly subsidizing outlets owned by politically connected companies. These findings highlight a *quid pro quo* through which political connections not only attract disproportionately high levels of state advertising but also incentivize media outlets to bias their news reporting to align with the government's interests.

The results further suggest that aligning with government interests entails audience costs for newspapers. Following the sale, two newspapers acquired by politically connected companies experience declines in circulations and losses in advertising space purchased by private entities. Nevertheless, despite these market penalties, their news reports continue to align with the government's preferences as they cover domestic economic news increasingly more positively relative to the control group, which did not experience any ownership change during the study period.

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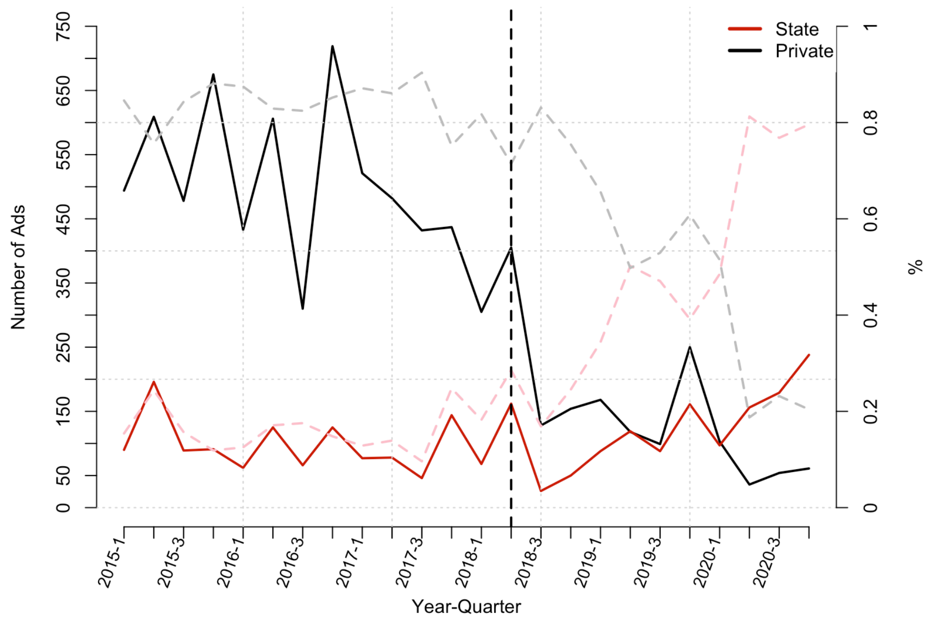
Appendix

A Advertising Data

A.1 Additional Results

Figure A.1: Quarterly Trend of the Number of Printed Ads



Note: Figure shows the contrast between trends in the total number of newspaper ads placed by state-owned and private banking institutions at every quarter. Dashed lines show the shares in total ad count with values indicated at the y-axis at the right. The vertical dashed line at 2018-02 indicates the quarter that contains the sale day (April 6, 2018).

Table A.1: Banking Sector Advertisers in the Sample

	Advertising Institution	Bank Type	Ads (2015 - 2020) Count	Space(col×cm)
1	Akbank	commercial	2,485	241,220
2	Garanti BBVA	commercial	1,635	210,404
3	Halkbank (*State-owned*)	commercial	1,142	189,171
4	İşbank	commercial	1,047	128,000
5	Ziraat Bank (*State-owned*)	commercial	731	108,075
6		participation	14	3,346
7	Vakıf Bank (*State-owned*)	commercial	638	119,984
8		participation	88	19,321
9	Yapı Kredi	commercial	650	116,523
10	TEB	commercial	600	92,061
11	ING	commercial	332	65,771
12	QNB Finansbank	commercial	312	56,129
13	Denizbank	commercial	261	48,113
14	Türkiye Finans Participation Bank	participation	175	25,027
15	Şekerbank	commercial	101	12,935
16	Odeabank	commercial	96	24,197
17	Albaraka Türk Participation Bank	participation	84	18,905
18	Fibabanka	commercial	84	9,389
19	Aktif Bank	investment	58	10,685
20	HSBC	commercial	44	7,255
21	ICBC (Tekstil Bank)	commercial	26	4,529
22	Burgan Bank	commercial	19	1,745
23	Bank Audi	commercial	15	1,626
24	The Participation Banks Association	-	14	1,991
25	The Interbank Card Center	-	12	1,603
26	Alternatif Bank (ABank)	commercial	8	678
27	Turk Eximbank (*State-owned*)	investment	8	436
28	Anadolubank	commercial	7	1,323
29	Citibank	commercial	6	76
30	TSKB	investment	3	307
31	Pasha Bank	investment	2	485
32	Deutsche Bank	commercial	1	212
	Total		10,698	1,521,522

Note: Table provides a list of banking sector institutions whose ads were printed at least once in one of the newspapers included in the study between 2015 and 2020. It shows the number of ads and their total space for each institution. When an advertiser is a bank, *Bank Type* indicates if it is classified as a commercial, investment or participation bank by Turkey's Banking Regulation and Supervision Agency (BRSA). There are three commercial, two participation and one investment banks that are state-owned in data, indicated in parenthesis.

Table A.2: Effect on Circulation

Dependent variable: $Circulation_{nt}$ (in millions)		
	Model 1	Model 2
$Sale$	-4.461	-0.660
	(1.161)	(0.209)
	[0.001]	[0.009]
$TreatmentPaper$	35.019	8.169
	(0.372)	(0.106)
	[0.000]	[0.000]
$Sale \times TreatmentPaper$	-5.103	-1.188
	(0.629)	(0.141)
	[0.027]	[0.020]
Num. obs.	217	962
$E(Circulation_{nt})$	26.925	6.176
$S(Circulation_{nt})$	13.634	3.117
Time	Month	Week
Bandwidth	-12:12	-52:52
Fixed Effects (ϕ_t, ψ_n)	Yes	Yes
Standard-errors: Clustered	Newspaper	Newspaper
R^2 (full model)	0.994	0.994
Adj. R^2 (full model)	0.993	0.994

Note: Unit of $Circulation_{nt}$ is a million. Regressions are estimated with a two-year bandwidth around the sale. Standard errors (in parenthesis) are clustered by newspaper. Wild Cluster Bootstrap p-values calculated with the Webb weights are in brackets.

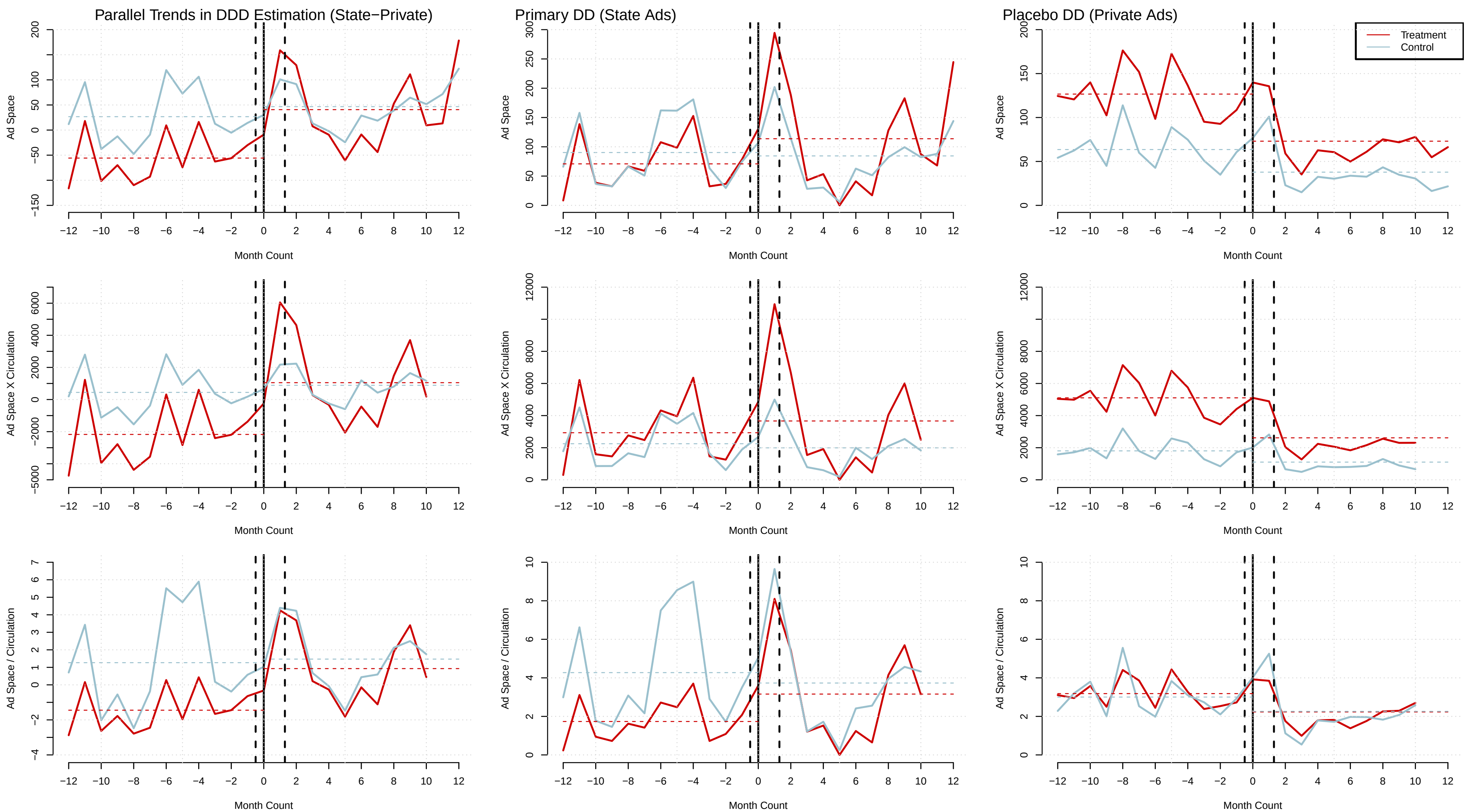
Table A.3: Placebo Regressions with Weekly Aggregated Data

Dependent Variable: *AdSpace*					
	Two years before	One year before	Baseline	One year after	Two years after
StateOwned	-110.479^{**}	-100.754^{**}	-66.981^{**}	-50.800^{**}	-52.220^{***}
	(24.046)	(21.376)	(14.295)	(10.654)	(8.572)
Sale	-12.585^{**}	-11.180^{**}	-9.843^{*}	-0.447	4.566
	(3.009)	(2.365)	(3.429)	(2.625)	(4.610)
TreatmentPaper	134.892^{***}	122.241^{***}	74.948^{***}	48.310^{***}	36.768^{***}
	(22.013)	(19.765)	(12.602)	(9.042)	(4.867)
$StateOwned \times Sale$	-2.597	-4.015	3.292	9.983	29.148
	(2.206)	(3.553)	(2.644)	(6.228)	(13.779)
$StateOwned \times TreatmentPaper$	-38.122^{***}	-28.140^{**}	-18.904^{**}	-3.008	-4.963
	(7.199)	(6.341)	(5.550)	(5.222)	(11.827)
$Sale \times TreatmentPaper$	-1.475	-2.064	-6.621^{*}	-3.610^{*}	-3.564
	(3.324)	(3.423)	(2.042)	(1.328)	(1.974)
$StateOwned \times Sale \times TreatmentPaper$	10.120	9.209	16.038^{***}	-1.197	-4.496
	(5.290)	(4.171)	(2.644)	(7.079)	(13.961)
Num. obs.	33600	33600	31584	28256	23296
Bandwidth(weeks)	-156:-52	-104:0	-52:52	0:104	52:142
Sale week	-104	-52	0	52	104
Clustered SE (Newspaper)	Yes	Yes	Yes	Yes	Yes
R^2 (full model)	0.187	0.169	0.132	0.114	0.144
Adj. R^2 (full model)	0.183	0.165	0.128	0.110	0.139

$^{**}p < 0.01$; $^{*}p < 0.05$

Note: Table shows the results of four placebo regressions (Columns 1-2 and 4-5) estimated with the baseline model for the advertising favors using Equation 1. Column 3 is the original model for reference. Placebo regressions are estimated with a two-year bandwidth around the placebo sale dates by shifting the actual sale date by 52 weeks. Standard errors (in parenthesis) are clustered by newspaper.

Figure A.2: Parallel trends in the Triple Difference Estimations and Their DD Components



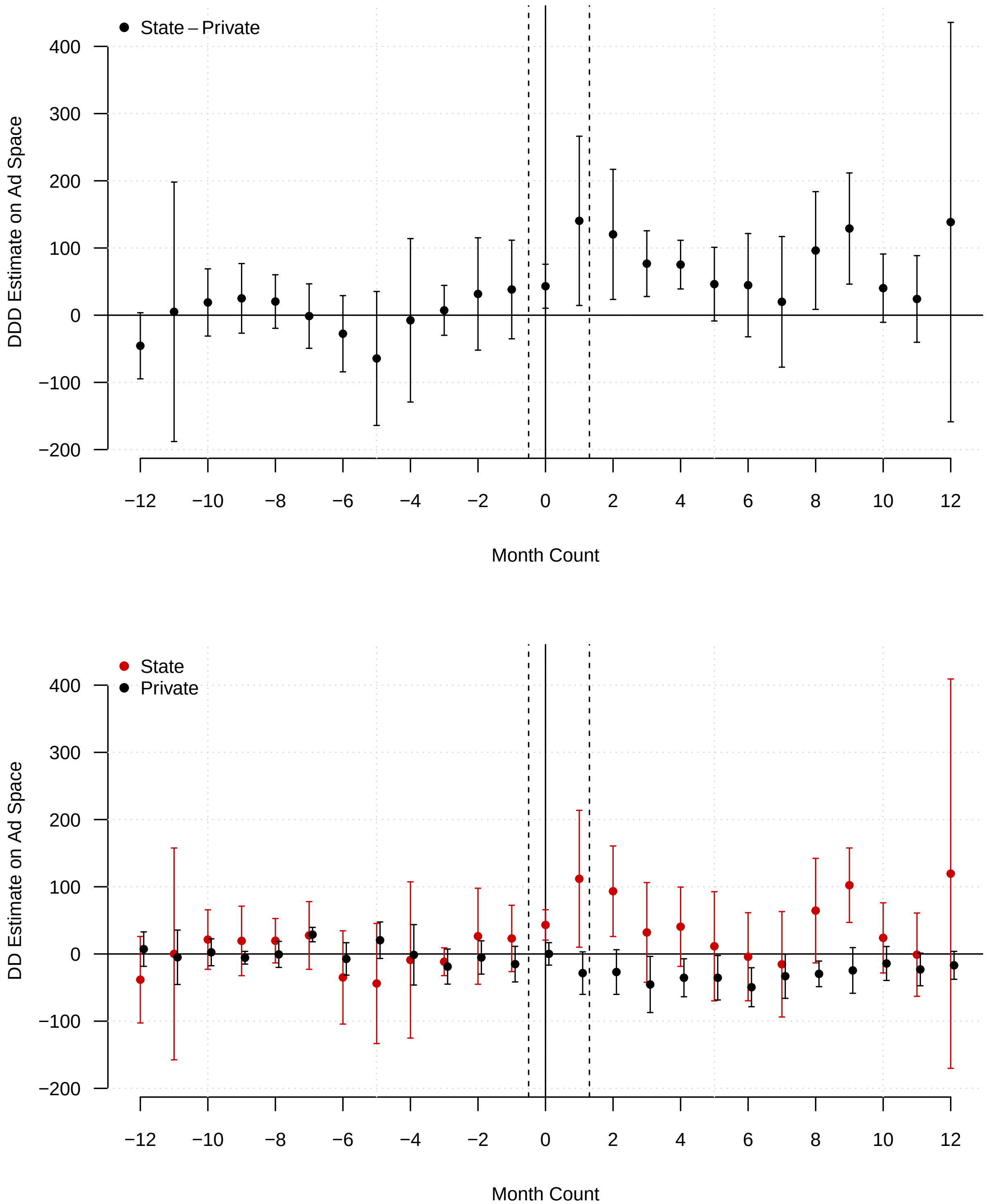
Note: Figure shows the parallel trends with three outcome variables, $AdSpace_{nat}$, $AdSpace_{nat} \times Circulation_{nt}$ and $\frac{AdSpace_{nat}}{Circulation_{nat}}$ used in the DDD models at Table 4 and the decomposition of the effect into the "Primary" DD and "Placebo" DD components. The outcome variables are aggregated monthly. The red (blue) lines represent the treatment (control) newspapers. The solid line marks the cut-off day when the sale was officially approved by the executive board of Doğan Media. The dashed lines show the day that the sale was publicly announced and the day that the sale was finalized. Horizontal dashed lines mark the average value of the difference in outcomes for the treatment and control groups in the pre- and post-treatment periods.

Table A.4: Results for Advertising Favors Accounting for Circulation (Monthly Data)

Dependent variable:	$AdSpace$ 1	$AdSpace$ 2	$AdSpace \times Circulation$ 3	$\frac{AdSpace}{Circulation}$ 4
$Circulation$		2.438		
		(1.526)		
		[0.151]		
$StateOwned$	−290.866	−293.967	−9018.455	−12.832
	(62.886)	(61.734)	(2954.195)	(1.982)
	[0.001]	[0.000]	[0.002]	[0.001]
$Sale$	−10.932	−6.962	−886.274	0.243
	(11.629)	(11.017)	(452.329)	(0.785)
	[0.370]	[0.595]	[0.046]	[0.967]
$TreatmentPaper$	333.690	256.777	11089.682	13.125
	(53.438)	(80.979)	(2486.419)	(1.599)
	[0.001]	[0.031]	[0.002]	[0.000]
$StateOwned \times Sale$	19.931	12.292	463.971	0.273
	(13.988)	(12.320)	(377.753)	(0.512)
	[0.171]	[0.339]	[0.262]	[0.585]
$StateOwned \times TreatmentPaper$	−82.460	−82.460	−2618.929	−2.715
	(24.348)	(24.339)	(540.551)	(1.538)
	[0.136]	[0.140]	[0.082]	[0.187]
$Sale \times TreatmentPaper$	−27.951	−15.837	−1745.343	−0.135
	(8.928)	(13.798)	(539.790)	(0.266)
	[0.116]	[0.444]	[0.082]	[0.646]
$StateOwned \times Sale \times TreatmentPaper$	76.558	74.165	2759.989	2.103
	(16.707)	(12.340)	(461.741)	(0.568)
	[0.066]	[0.044]	[0.044]	[0.094]
Num. obs.	7488	6944	6944	6944
Time	Month	Month	Month	Month
Bandwidth (Sale week = 0)	−12 : 12	−12 : 12	−12 : 12	−12 : 12
Fixed Effects (ϕ_t, γ_a, ψ_n)	Yes	Yes	Yes	Yes
Clustered SE (Newspaper)	Yes	Yes	Yes	Yes
Num. groups: Newspaper	10	10	10	10
Num. groups: Advertiser	32	32	32	32
R^2 (full model)	0.293	0.305	0.298	0.212
Adj. R^2 (full model)	0.286	0.298	0.292	0.204

Note: Table shows the regression results with the triple difference model using month-newspaper-advertiser level data. Standard errors (in parenthesis) are clustered by newspaper. Wild Cluster Bootstrap p-values calculated with the Webb weights are in brackets.

Figure A.3: Event Studies for the Triple Difference and Its Double-Difference Components



Note: The figure plots coefficients from event study specifications with fully interacted month dummies, estimated on the month-newspaper-advertiser data with a 12-month bandwidth around the sale. The top panel shows the dynamic triple difference, and the bottom panel decomposes it into the primary DD among state-owned advertisers and the placebo DD among private advertisers, whose vertical distance in each month is the triple-difference estimate above. All specifications include newspaper, advertiser and month fixed effects. Coefficients are normalized to the pre-treatment average so, every month receives a point estimate. Vertical bars are 95% confidence intervals from standard errors clustered by newspaper. The solid line marks the executive board approval of the sale; the dashed lines mark the public announcement and the final takeover by Demirören.

A.2 Banking Sector in Total Newspaper Advertising

Table A.5: The Share of Sample in Total Advertising Data by Newspapers

Newspaper	SOEs' Ad Space (2015) Commercial Banks (Interpress)	11 SOEs (Yanatma (2021))	%	All Advertisers' Ad Space (2015) Banking Sector Ads (Interpress)	Total Ad Space (Yanatma (2021))	%
Cumhuriyet	0	3,548	0	17,911	748,381	2.4
Habertürk	8,316	N/A	N/A	43,128	N/A	N/A
Hürriyet	3,353	40,894	8.2	60,772	9,856,831	0.6
Milliyet	10,492	53,440	19.6	31,890	3,250,504	1.0
Posta	2,847	27,327	10.4	44,232	4,580,154	1.0
Sabah	18,225	105,481	17.3	69,779	6,408,749	1.1
Sözcü	0	244	0	24,644	1,265,844	1.9
Takvim	12,771	77,712	16.4	23,286	999,711	2.3
Türkiye	14,138	64,726	21.8	27,242	1,026,900	2.7
Vatan	9,817	45,198	21.7	19,591	1,179,793	1.7
Total	71,643	418,570	17.1	319,347	29,316,867	1.08

Note: 11 SOEs in 2015 whose total ad space Yanatma (2021) reports are Turkish Airlines, TOKI, Emlak Konut GYO, Turk Telekom, Avea, TTNet, Turkcell, Digiturk, Ziraat Bankasi, Halkbank, and Vakifbank. Three of them are state-owned banks, and the second column shows their total ad space in 2015 in each newspaper calculated using the Interpress data. Similarly, the last three columns show the ad space by all banking institutions listed in Table A.1 compared to the total space allocated to advertising in each newspaper in 2015. Values in the total row are calculated excluding Habertürk.

This section compares the advertising space used by the banks to total advertising space in the newspapers included in the analysis to outline how my sample stands with respect to total advertising. Data for total advertising comes from the replication package of Yanatma (2021) which overlaps only one year with my sample. Since his data is at year-newspaper level, it does not allow for a detailed analysis. Additionally, he reports total ad space used by the most frequently advertising 11 state-owned enterprises (SOEs) without providing advertiser-level distribution. His data does not cover Habertürk newspaper and the years after 2015.

Three commercial state-owned banks (Ziraat Bank, Halk Bank and Vakif Bank) are among the 11 SOEs that advertise in printed newspapers regularly. The left panel of Table A.5 compares the distribution of ads by the three state-owned banks in my data (sourced from Interpress) to that by the 11 SOEs in Yanatma (2021). On average, state-owned banks account for 17.1% of the total advertising space used by 11 SOEs in newspapers of interest.

We can observe in Table A.5 that in 2015, state-owned banks had newspaper preferences similar to other state-owned enterprises (SOEs). Two opposition newspapers, Cumhuriyet and Sözcü, which did not receive any advertising from state-owned banks, were also the least preferred newspapers by the other eight SOEs. Their top three choices - the conservative newspapers (Sabah, Takvim, and Türkiye) - overlapped as well.

In contrast, the right panel indicates that in data including ads by private enterprises, the most preferred outlets are the mainstream newspapers (Hürriyet and Posta) owned by the Doğan Media in 2015, and one conservative outlet (Sabah) with high circulation. Although Hürriyet was the top choice of private advertisers by a large margin, SOEs preferred all newspapers owned by a politically connected conglomerate over Hürriyet.

A.3 Content of Ads

Figure A.4 shows example ads printed in the 12/19/2017 issue of Hürriyet newspaper. The issue is downloaded from PressReader. On the left panel is an ad by the state-owned Vakifbank and the right panel is an ad by the private Garanti Bank. Data I use for the analysis is provided by Interpress, and I do not have visuals for the other observations. For the ads presented in Figure A.4, Interpress data records "Vakıfbank" and "Garanti Bankası" as product names (*Urun*). For both ads, ad type is promotional ad (*Tanitici Reklam*). I also have the title texts in my data set, which can be translated as "We are with you to meet all your needs with the New Year Loan" (Vakifbank) and "The loan that turns small business owners' winter to spring" (Garanti Bank). The Interpress data does not contain the remaining texts featured in the ads under their titles.

I analyze ad titles using a multinomial Naive Bayes classifier to evaluate whether there is a systematic difference in words used in state-owned and private banks' ads. To prepare text data for the NB classifier, I drop stop words [47], bank names, numbers, and punctuations from titles. Using a Turkish NLP package, *Zemberek*[48], I stem the words and convert them

[47]Turkish stopwords are downloaded from github.com/Alir3z4/python-stop-words
[48]Available at github.com/Loodos/zemberek-python

to lowercase. I construct a document-term matrix with the remaining normalized words (terms hereafter) using the count vectorizer in *sklearn* package in Python following the expected application in the documentation of *MultinomialNB*[49] in the same package. Using the TF-IDF vectorizer following the same pre-processing steps returns similar results. The vectorization accounts for uni-grams and bi-grams.

I use all titles to fit the model since I am using it to get the terms with top conditional probabilities rather than to predict more texts. As a result, I have $10,698$ documents (titles) and 5080 terms in the document-term matrix I used to fit the NB classifier. Out of $10,698$ documents, 8077 belong to *private* and 2621 belong to *stateowned*, which results in the prior probabilities, $P(private) = 0.755$ and $P(stateowned) = 0.245$. Conditional probability $P(t|c)$ of a term, t, is the likelihood of t given a class c, which is estimated as the relative frequency of t in documents belonging to c, where $c \in \{stateowned, private\}$.

$$\hat{P}(t|c) = \frac{T_{ct}}{\sum_{t' \in V} T_{ct'}} \tag{6}$$

T_{ct} is the count of occurrences of t in titles belonging to c[50]. Table A.6 lists top 25 terms based on their likelihood given a class, *stateowned* or *private*.

[49] scikit-learn.org/1.5/modules/generated/sklearn.naive_bayes.MultinomialNB.html

[50] nlp.stanford.edu/IR-book/html/htmledition/naive-bayes-text-classification-1.html

Table A.6: Top 25 Terms (Word Stems) Predicting Titles of State-owned and Private Advertisings Ordered by Their Conditional Probabilities

	Term	$P(Term\|State\_owned)$	Term	$P(Term\|Private)$
1	**kobi** *(SME)*	0.020	**kredi**	0.025
2	**kredi** *(loan)*	0.016	tl *(Turkish Lira)*	0.010
3	iste *(want)*	0.015	yatırım *(investment)*	0.010
4	paraf	0.014	emekli *(retired)*	0.008
5	bankkart	0.011	mobil *(mobile)*	0.007
6	**ihtiyaç** *(need)*	0.008	**türkiye**	0.007
7	**yıl** *(year)*	0.008	**yıl**	0.006
8	**bayram** *(holiday)*	0.007	**yeni**	0.006
9	**türkiye** *(Turkey)*	0.007	**kobi**	0.006
10	**esnaf** (small business owner)	0.006	faiz *(interest)*	0.006
11	paraf kobi	0.006	**bayram**	0.006
12	leasing	0.005	altın *(gold)*	0.005
13	fazla *(more)*	0.005	öde *(pay)*	0.005
14	**yan** *(side)*	0.005	**esnaf**	0.005
15	gün *(day)*	0.004	**yan**	0.005
16	şampiyon *(champion)*	0.004	fırsat *(opportunity)*	0.005
17	destek *(support)*	0.004	hesap *(account)*	0.005
18	kart *(card)*	0.004	bugün *(today)*	0.005
19	iş *(work)*	0.004	cep *(pocket)*	0.004
20	el *(hand)*	0.004	**dünya**	0.004
21	büyü *(grow)*	0.004	fon *(fund)*	0.004
22	**dünya** *(world)*	0.003	kazan *(gain)*	0.004
23	**yeni** *(new)*	0.003	**ihtiyaç**	0.004
24	çiftçi *(farmer)*	0.003	başla *(start)*	0.004
25	büyüt *(make grow)*	0.003	hediye *(gift)*	0.004

Note: The table shows conditional probabilities of top 25 terms occuring in ad titles of state-owned and private banks. Terms common to both classes are in bold text. English translations are in parenthesis. Terms, *paraf* and *bankkart* are not translated since they are the proper names of credit cards of Halk Bank and Ziraat Bank.

Figure A.4: Examples of state-owned and private bank advertising on newspaper

Note: Figure shows a VakifBank (state-owned) and a Garanti Bank (private) ad printed in the 12/19/2017 issue of Hürriyet newspaper downloaded from PressReader. The title of the VakifBank ad translates as "We are with you to meet all your needs with the New Year Loan." Below the title, it says "New Year Loan is here with favorable interest rates and easy repayment options." The title of the Garanti Bank ad can be translated as "The loan that turns small business owners' winter to spring." The sentence under the title states that "Thanks to the Commercial Installment Loan with a three-month grace period, small business owners and SMEs can cover their needs in December and begin repayment in the spring."

B News Data

B.1 Additional Results

Table A.7: DID Results for Coverage Favors

Outcome: $Sentiment_{nt}$						
	1	2	3	4	5	6
Treatment	0.115^{**}	0.117^{**}	0.117^{**}	0.127^{**}	0.125^{**}	0.137^{**}
	(0.029)	(0.031)	(0.032)	(0.029)	(0.026)	(0.026)
Num. obs.	10312	10312	1534	1534	400	400
Num. groups: Day	1095	1095				
Num. groups: Week			154	154		
Num. groups: Month					40	40
Num. groups: Newspaper	10	10	10	10	10	10
Controls	No	Yes	No	Yes	No	Yes
Fixed Effects (ϕ_t, ψ_n)	Yes	Yes	Yes	Yes	Yes	Yes
Clustered SE (Newspaper)	Yes	Yes	Yes	Yes	Yes	Yes
R^2 (full model)	0.500	0.502	0.728	0.735	0.883	0.887
Adj. R^2 (full model)	0.440	0.442	0.695	0.703	0.866	0.870

$^{**}p < 0.01$; $^{*}p < 0.05$

Note: Table shows DID regression results using the average sentiment scores aggregated at newspaper-time(day, week, or month) levels. Model 2, 4, and 6 control for newspaper-time level controls, number of news reports and average number of words.

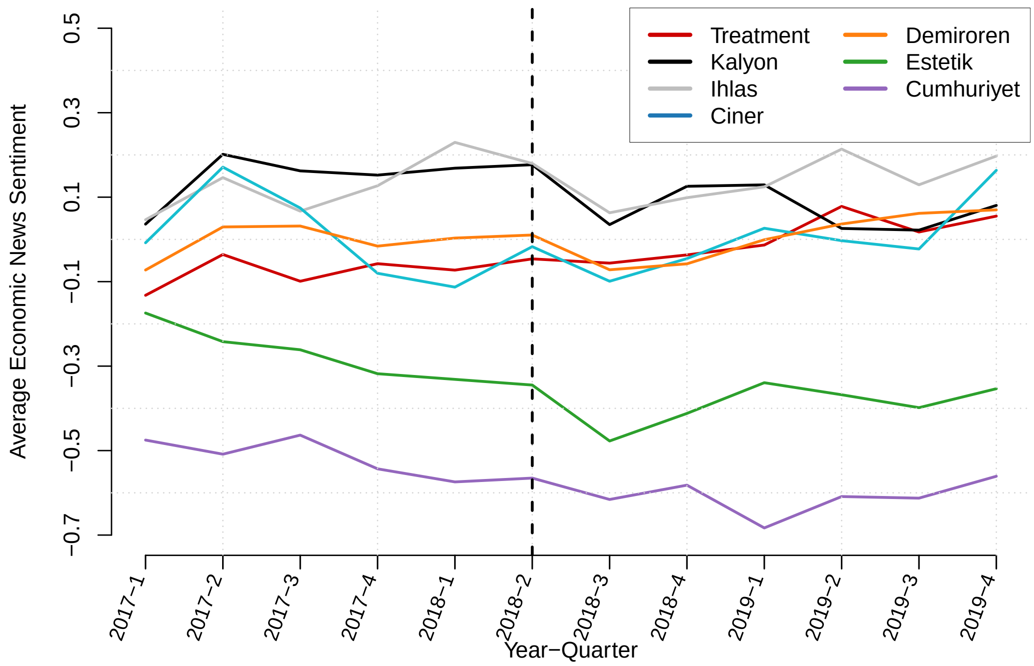
Table A.8: DID Results for Coverage Favors Leaving a Newspaper Out

	Baseline	wo/Cumhuriyet	wo/Sözcü	wo/Habertürk	wo/Milliyet	wo/Vatan	wo/Sabah	wo/Takvim	wo/Türkiye
Treatment	0.119^{**}	0.113^{**}	0.106^{**}	0.122^{**}	0.122^{**}	0.130^{**}	0.121^{**}	0.111^{**}	0.127^{**}
	(0.031)	(0.033)	(0.030)	(0.034)	(0.034)	(0.031)	(0.034)	(0.032)	(0.033)
Num. obs.	1540	1386	1386	1386	1386	1386	1386	1386	1386
Num. groups: Week	154	154	154	154	154	154	154	154	154
Num. groups: Newspaper	10	9	9	9	9	9	9	9	9
Controls	No	No	No	No	No	No	No	No	No
Fixed Effects (ϕ_t, ψ_n)	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Clustered SE (Newspaper)	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
R^2 (full model)	0.858	0.728	0.847	0.866	0.863	0.869	0.845	0.883	0.887
Adj. R^2 (full model)	0.841	0.692	0.827	0.849	0.845	0.851	0.824	0.867	0.872

$^{**}p < 0.01$; $^{*}p < 0.05$

Note: Table presents DID regression results with Equation 5 using data at the week-newspaper level and excluding one control newspaper at a time. The outcome is 4-week moving average of sentiment scores. It shows that the baseline results at Column 2 of Table 6 are not driven by any newspaper by itself.

Figure A.5: Quarterly Trend in Sentiment Score by Owner Companies



Note: Figure shows the average sentiment score in newspapers in quarters by their owners. Dashed line at 2018-02 indicates the quarter that contains the sale day (April 6, 2018).

Table A.9: Descriptive Statistics for the Sentiment Scores

Statistic	N	Mean	St. Dev.	Min	Max
Sentiment	1,540	−0.061	0.238	−0.785	0.557
Sentiment|Treatment	308	−0.034	0.093	−0.390	0.152
Sentiment|Control	1,232	−0.068	0.261	−0.785	0.557
Sentiment|Sabah	154	0.190	0.063	−0.102	0.311
Sentiment|Türkiye	154	0.139	0.165	−0.747	0.557
Sentiment|Takvim	154	0.026	0.137	−0.334	0.496
Sentiment|Milliyet	154	0.026	0.076	−0.142	0.197
Sentiment|Habertürk	154	0.003	0.096	−0.160	0.231
Sentiment|Hürriyet	154	−0.013	0.067	−0.212	0.152
Sentiment|Vatan	154	−0.024	0.081	−0.201	0.176
Sentiment|Posta	154	−0.055	0.108	−0.390	0.129
Sentiment|Sözcü	154	−0.332	0.099	−0.504	0.003
Sentiment|Cumhuriyet	154	−0.570	0.095	−0.785	−0.324

Note: Table shows the summary statistics for the 4-week moving averages of sentiment scores with the newspaper-week level data.

B.2 Topic Classification with BERT

The labels used in fine-tuning are the web site sections in which news reports were published and extracted with *lxml* package in Python. 80% of the news articles with a known news section is used to fine-tune BERT on the classification task. The remaining 20% are split equally for validation after each epoch and test at the end of the fine-tuning procedure. Table A.10 shows the performance metrics for the region and topic models with the validation and test data sets. Table A.11 is the confusion matrix using the test data. We see that BERT performed with very high accuracy, precision, and recall with this data set. News articles that fall into the intersection of the *economy* and *Turkey* labels are used in the analysis. Section B.3 evaluates whether relevant articles are precisely selected in the analysis data using human-coded labels.

Table A.10: Model Performance Metrics

Data	**Metric**	**Economy**	**Sports**	**Other**	**Weighted**	**Turkey**
Validation	Accuracy	0.9806	0.9952	0.9774	0.9766	0.9865
	F1	0.9496	0.9929	0.9761	0.9766	0.9905
	Precision	0.9479	0.9926	0.977	0.9766	0.9837
	Recall	0.9513	0.9933	0.9751	0.9766	0.9973
Test	Accuracy	0.9805	0.9954	0.9774	0.9766	0.988
	F1	0.9496	0.9931	0.9759	0.9766	0.9916
	Precision	0.9464	0.9922	0.9779	0.9766	0.9855
	Recall	0.9529	0.9941	0.9739	0.9766	0.9977

Table A.11: Confusion Matrix with Test Data

True\Predicted	**Economy**	**Sports**	**Other**
Economy	20661	42	980
Sports	44	37467	180
Other	1125	253	51447

B.3 Human Validation of Text Methods

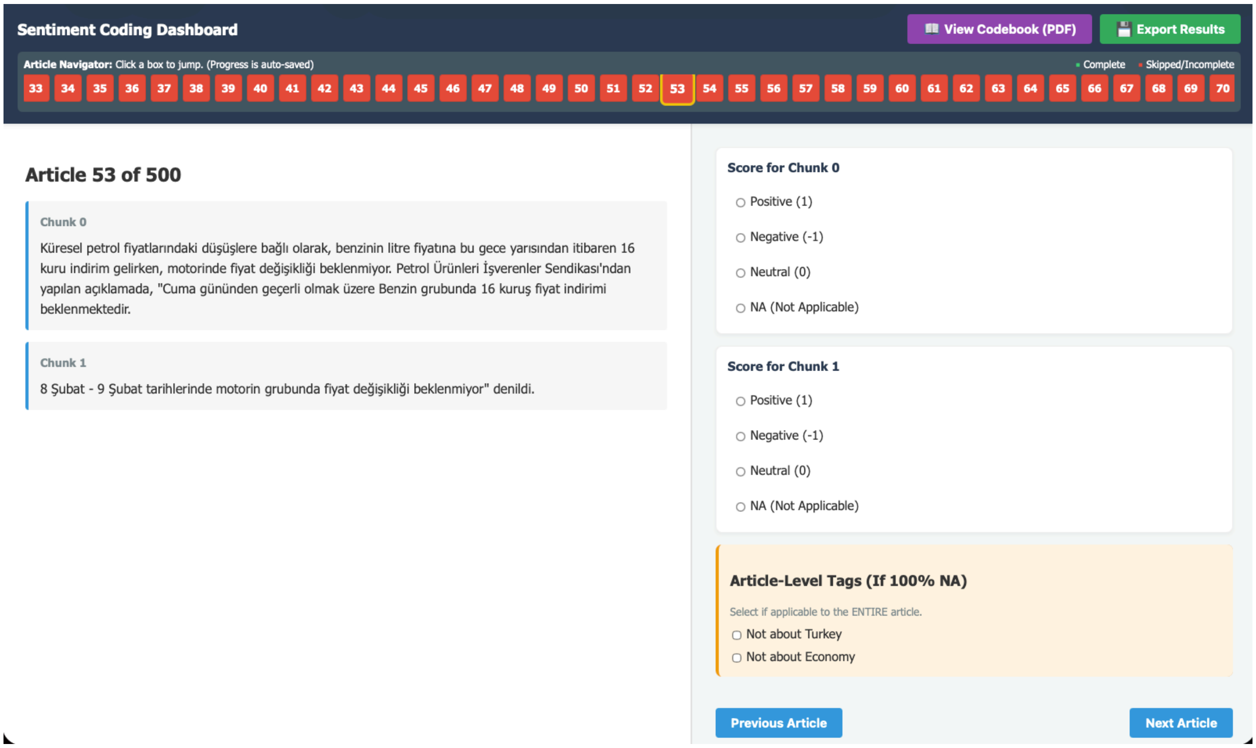
The text methods used in this paper follow an automated procedure that requires human review to ensure the quality of the final data set and predicted variables. First, I retrieve the HTMLs from the CC-MAIN and CC-News archives of Common Crawl. The news texts and website sections extracted from these HTMLs are used to finetune BERT classifiers. This procedure classifies 416,881 news articles into *economy* and *Turkey* categories, which constitutes the analysis data (Table 3). Then, I use GPT-4o-mini to compute the sentiment scores at the article-level for the analysis.

I hired an independent coder to validate the analysis data. The coder manually annotated 500 news articles randomly selected from 416,881 news articles. The newspaper names are hidden from the coder. He read the articles split into chunks, as used in the GPT prompts, and assigned a score, positive (1), negative (-1), neutral (0), or NA, for each. The average of chunk scores after excluding NA chunks is the article's sentiment score. The coder is instructed to assign the score based on the information in the chunk only; however, he would naturally be aware of the context of the news report as reading its chunks in order. I avoid presenting shuffled chunks, since the human-coding procedure is meant to be similar to the real-life news reading experience. All coding instructions are given in Section C. In addition to the sentiment scoring, the coder is also instructed to label whether a news article is not about Turkey or economy and flag parsing errors and non-news content, if he encounters any, to detect the false positives in the analysis data. Figure A.6 shows the interface presented to the coder to complete the task.

B.3.1 Validation of HTML Parsing and BERT

The effect of parsing errors on the final data set is minimal; approximately 2% of the analysis data is affected. The web crawl data are inherently noisy due to various obstacles to extract the text of interest such as non-standard HTML formatting and incomplete loading. Moreover, the Common Crawl repository includes URLs that do not point to a news article,

Figure A.6: Human Annotation Interface



which requires further cleaning. The coder reviewed the 500 articles and determined that 13 of them are not news reports. They feature texts extracted from wrong parts of the corresponding HTMLs, such as lists of news titles or unfinished sentences. Titles usually indicate economic news, so they are not filtered out by the BERT model. However, only 11 of them would remain in the final data set, as GPT labels the other two as NA. The average sentiment score of these records is -0.09. I also find 33 records sharing company announcements citing the website of Turkey's public disclosure platform, rather than writing a news report on the announcements. Such information disclosures without journalistic reporting are approximately 7% of the data set and have mostly neutral scores.

I exclude the parsing errors to compute the precision of the BERT-based topic models. The analysis data includes news articles labeled (published under sections related to economy and Turkey) or predicted to be about the Turkish economy. The precisions of the topic models are exceptionally high above 93%. Among 487 news articles after excluding the parsing errors, the coder labeled 18 false positives for the *economy* topic and 34 false positives for *Turkey* topic resulting in precision levels at 96.3% and 93.02%, respectively. Also note that 6 out of 18 false positives on the *economy* topic and 14 out of 34 false positives on *Turkey* topic are eliminated since GPT assigned them NA increasing the precision of the analysis data to 97.5% for the *economy* indicator and 95.8% for the *Turkey* indicator.

B.3.2 Validation of Sentiment Scores with GPT

The coder assigned a sentiment score for each chunk of a news report as shown in Figure A.6. Article-level sentiment scores are calculated as the average of chunk scores. Figure A.7 shows a strong article-level alignment between GPT scores and human coded scores. The correlation between human-coded sentiment and GPT sentiment is 0.77 using pairwise non-NA article scores and 0.74 recoding the NAs as zero.

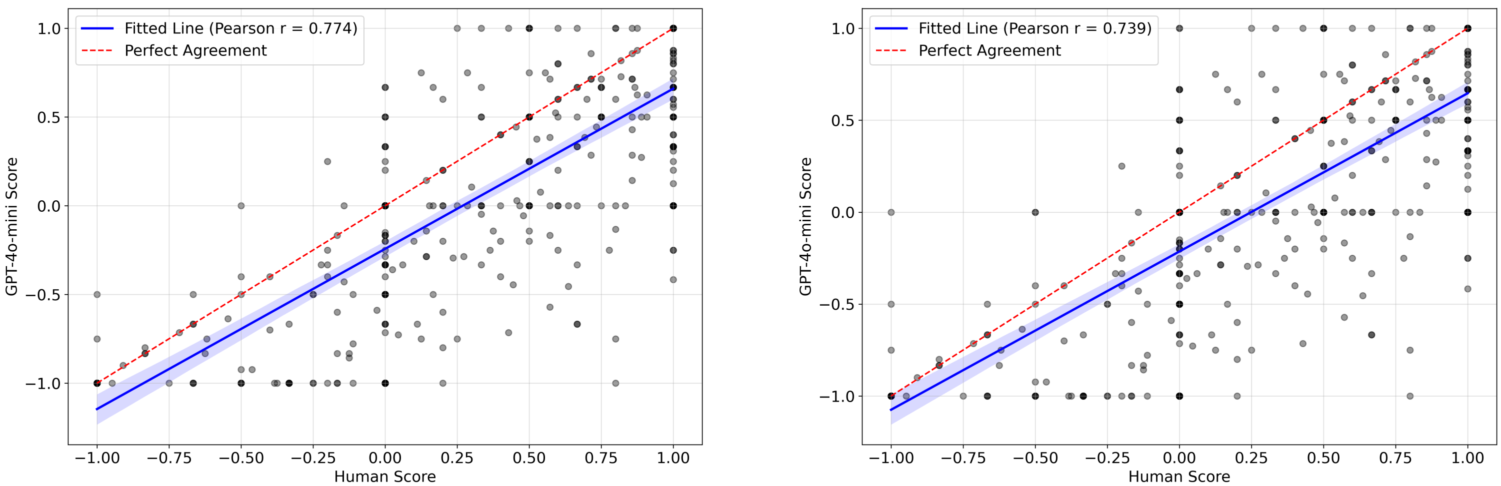
Although human sentiment scores successfully follow the overall trajectory of human sentiment, the fitted linear regression line for human sentiment scores illustrates a downward shift from the 45-degree line, indicating a mild negativity bias in the GPT scores. The human annotator skewed towards positive extremes, while GPT penalized the text more symmetrically, effectively shifting the overall average sentiment downwards by approximately 0.24 points relative to the human baseline.

Table A.12 highlights this pattern by mapping continuous article scores into directional categories. GPT exhibits a high precision for positive sentiment (92%). Of the 184 articles GPT scored as positive, the human coder agreed in 169 cases, yielding a precision rate of approximately 92%. On the other hand, the negative category has a very high recall (93%), but low precision (43%). For both negative and neutral labels, the disagreement between the coder and GPT is predominantly in the positive direction.

Figure A.7: Correlation of Human-Coded and GPT Article Scores

(a) Pairwise Complete Observations

(b) NA=0



Note: Figures show the correlation of article scores coded by GPT and the human coder excluding NAs (left) and assigning a zero score to NAs (right). The 45-degree (red) indicates perfect agreement between human-coded scores and GPT.

Table A.12: Confusion Matrix of Human vs. GPT Sentiment Scores

		GPT Score				
		Negative	Neutral	Positive	NA	All
Human Score	Negative	71	2	1	2	76
	Neutral	42	47	10	10	109
	Positive	42	33	169	6	250
	NA	11	17	4	20	52
	All	166	99	184	38	487

Note: This table presents the confusion matrix after recoding the continuous article scores into discrete sentiment categories. Rows represent the ground-truth scores provided by the human annotator, and columns display the predicted scores generated by the GPT model. The diagonal cells capture instances of exact agreement between the human and the model. Off-diagonal cells indicate mismatches, highlighting where the model over- or under-predicts an article's sentiment score, and the "All" row/column provides the marginal totals for each category. 13 records with parsing errors are excluded.

Since the downstream analysis the SDID with newspaper and time fixed effects, the only channel through which a measurement error in the outcome variable can bias the estimate of the treatment effect is when the errors are differential across treatment and control groups and time. Hence, we need to show that the error is not associated with the treatment.

Let Y^*_{nt} be the human sentiment score of news reports in newspaper n published at time t, and Y_{nt} be the GPT-generated sentiment. The GPT error is $e_{nt} = Y_{nt} - Y^*_{nt}$. Ignoring the time and unit weights in SDID, which require a balanced panel to estimate, the bias in the treatment effect estimated with GPT scores, $\hat{\tau}_{GPT}$, is,

$$Bias = [E(e_{Treatment,Post}) - E(e_{Treatment,Pre})] - [E(e_{Control,Post}) - E(e_{Control,Pre})]$$

Then, γ_3 is an estimate for the bias:

$$e_{nt} = \alpha + \gamma_1 TreatmentPaper_n + \gamma_2 Sale_t + \gamma_3 (TreatmentPaper_n \times Sale_t) + u_{nt}$$

Table A.13 presents the results of this regression at the newspaper-week level (Column 1), which aligns with the aggregation in the primary SDID specification, as well as at the article level (Column 2). The highly significant intercept ($\alpha = -0.242$) formally captures the structural negativity bias of the GPT model. Crucially, the coefficient on the interaction term, γ_3, is estimated to be very close to zero (-0.003) and is statistically insignificant. The results confirm that the measurement error is orthogonal to the treatment. Because the differential error across treatment status and time is indistinguishable from zero, the GPT's bias operates as a level effect, ensuring that the downstream causal estimates remain robust and unbiased.

Table A.13: Effect of Treatment on Measurement Error in Sentiment Scores

Dependent Variable:	GPT_error_{nt}	$GPT\_error_{article}$
	1	2
$Intercept$	-0.242^{**}	-0.249^{**}
	(0.046)	(0.039)
$Sale$	-0.078	-0.058
	(0.056)	(0.043)
$TreatmentPaper$	0.012	0.053
	(0.047)	(0.039)
$Sale \times TreatmentPaper$	-0.003	-0.053
	(0.063)	(0.047)
Num. obs.	327	417
Time	Week	
Fixed Effects	No	No
Clustered SE (Newspaper)	Yes	Yes
Num. groups: Newspaper	10	10
R^2 (full model)	0.010	0.010
Adj. R^2 (full model)	0.001	0.003

$^{**}p < 0.01$; $^{*}p < 0.05$

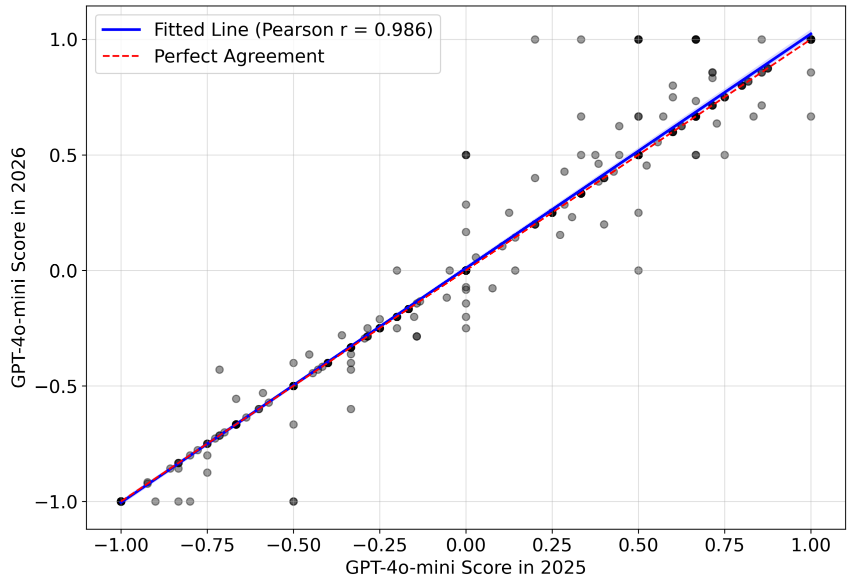
Note: The dependent variable is the GPT measurement error ($e_{nt} = Y_{nt} - Y^*_{nt}$), calculated as the difference between the GPT-generated sentiment score and the human-coded score. Column 1 estimates the model using data aggregated to the newspaper-week level, matching the unit of analysis in the primary SDID model. Column 2 estimates the model at the article level. Standard errors are clustered at the newspaper level and reported in parentheses.

B.4 Replicability GPT Scores

Sentiment scores are generated using the chat completion method of OpenAI's Python package with GPT-4o-mini-2024-07-18 between 09/18/2025 and 09/20/2025. I configure the chat completion arguments to run the model as deterministically as possible by setting the temperature to zero and fixing the seed number. I also save the system fingerprint from the GPT response for every chunk. System fingerprints allow users to observe whether there is any change in the environment that the model is run even though a typical user would not have any control over it. I repeat the same procedure, using the same model and configuration, with the randomly selected 500 articles on 04/16/2026 to reproduce the GPT scores.

The temporal reproducibility of the metrics is plotted in Figure A.8. Despite the changes

Figure A.8: Replication of GPT Scores



Note: The scatter plot maps the average article-level sentiment calculations executed in September 2025 against the identical replication pipeline executed in April 2026. The high concentration of values along the perfect diagonal reinforces the consistency of the classification procedure.

in OpenAI's system fingerprints, the original 2025 scores and the 2026 replication runs exhibit an almost perfect linear alignment with a Pearson correlation coefficient of 0.986[51]. This high degree of stability confirms that configuring zero temperature alongside a rigid seed parameter successfully limits model stochasticity, establishing long-term computational replicability for large-scale text classification frameworks, provided that the underlying model is available.

[51]Replacing NA article scores with zeroes yields an approximately equal correlation coefficient.

B.5 Examples of Framing and Selection in Economic News

B.5.1 Coverage of 2017 Referendum and Its Economic Impact

Table A.14 shows examples of a positive, negative, and neutral chunk in its original language and English. Examples are selected from news articles published several weeks before the critical constitutional referendum on 14 April 2017, where the "yes" vote means the approval of the presidential system proposed by the AKP government, replacing the existing parliamentary regime. The opposition criticized the proposed regime as it would consolidate excessive power at the president's office, institutionalizing "the one-man system" that Erdoğan aspires to.[52]

Each example reports on the Turkish economy in relation to the upcoming referendum. The first chunk is taken from the opposition newspaper, Sözcü, which reports a suspicious increase in secret service expenditures by 65%, implying the government's excessive use of public resources for campaigning. This text is scored negative, and the explanation shows that the model understands the content and tone of the text. In contrast, the second chunk from the pro-government Sabah daily presents a clearly positive tone, linking a "yes" vote to economic stability and growth. The model accurately interprets this text as positive and captures its main message. The first two examples also take a clear political stance presuming that voters care about economic conditions. The third chunk, sourced from Hürriyet, focuses on the uncertainty in pricing without any positive or negative statement due to the unpredictability of the referendum outcome. The model identifies this chunk as neutral. The explanations in the responses indicate that GPT captures the key points of the news reports and correctly evaluates the tone[53].

[52] https://www.brookings.edu/articles/the-turkish-constitutional-referendum-explained/

[53] A systematic assessment of sentiment scores will be added after a human-coded sample of news data is prepared.

Table A.14: Example Article Chunks and GPT Responses

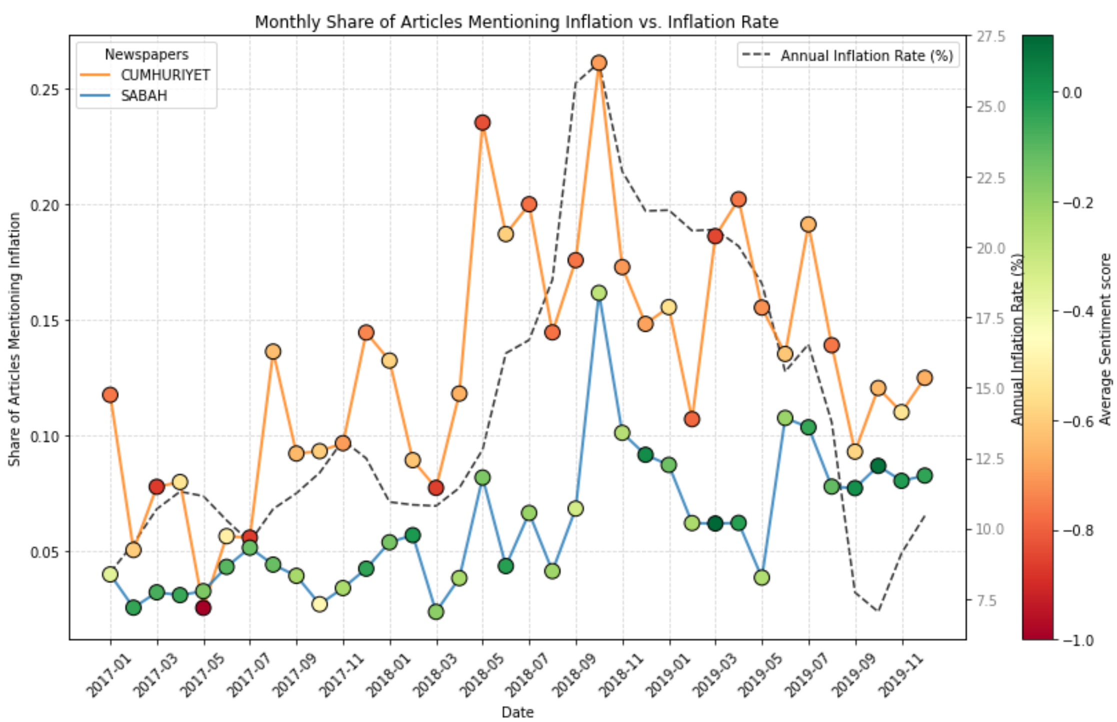
	Chunk Text	**Translation**
Newspaper: Sözcü **Date:** 2017-03-16 **Word Count:** 40 **GPT Response:** Category: negative, Explanation: Increased spending indicates concerns.	Gizli hizmet giderleri şubat ayında yüzde 65 artarak 282 milyon 263 bin liraya yükseldi. Referandum öncesi örtülü harcamalardaki hızlı yükseliş dikkat çekti .. Hemen her seçim öncesinde olduğu gibi bu yıl yapılacak referandum öncesinde de örtülü ödenek harcamalarında tırmanış yaşandı.	Expenditures on covert services increased by 65 percent in February to 282 million 263 thousand liras. The rapid increase in secret expenditures before the referendum drew attention. As in the run - up to almost every election, there has been a surge in the expenditures of the secret appropriation before the referendum to be held this year.
Newspaper: Sabah **Date:** 2017-03-03 **Word Count:** 50 **GPT Response:** Category : positive , Explanation: Promises economic stability and growth .	Referandumda 'evet'in ekonomiye istikrar kazandıracağını söyleyen Başbakan Yardımcısı Canikli, "Sermaye girişi artacak, enflasyon gerileyecek, Türkiye üst lige çıkacak" dedi Başbakan Yardımcısı Nurettin Canikli, referandumda "evet" oyunun ekonomiye kazandıracaklarını SABAH'a anlattı.	Stating that 'yes' in the referendum will stabilize the economy, Deputy Prime Minister Canikli said, "Capital inflows will increase, inflation will decline, Turkey will be in the top league." Deputy Prime Minister Nurettin Canikli told SABAH what a "yes" vote in the referendum will bring to the economy.
Newspaper: Hürriyet **Date:** 2017-04-06 **Word Count:** 55 **GPT Response:** Category: neutral, Explanation: Discusses political context, not economy.	AKP ve MHP'nin desteklediği düzenlemeye, CHP ve HDP karşı çıkıyor. Referanduma iki haftadan kısa bir süre kalmasına karşın anketler birbirine oldukça yakın sonuçlara işaret ediyor. ABD seçimleri ve Brexit'i örnek gösteren bankacılar, anketlerin birbirine çok yakın olduğu bir ortamda net bir sonuç tahmin etmenin ve buna göre fiyatlama yapmanın hiç de kolay olmadığını belirtiyorlar.	The CHP and HDP oppose the amendment supported by the AKP and MHP. Although the referendum is less than two weeks away, the polls point to very close results. Citing the US elections and Brexit as examples, bankers state that it is not easy to predict a clear outcome and price accordingly in an environment where the polls are so close to each other.

Note: Table shows three news chunks reporting Turkish economy ahead of the constitutional referendum held on 14 April 2017, where the "Yes" vote means the approval of the proposed presidential system, harshly criticized by the opposition party on accounts that it would allow Erdoğan to consolidate his power. The first column shows variables regarding the chunk and article it is taken from along with the GPT response to the prompt. The second column shows the chunk in Turkish as it is inserted in the prompts. The third columns is the same chunk translated to English with DeepL.

B.5.2 Coverage of Inflation

Figure A.9 visualizes the divergence in the selection and framing of inflation-related coverage in two newspapers that polarize the most in my dataset (Table A.9), together with the official inflation rate reported every month. Throughout the observed period, Cumhuriyet, consistently allocates a larger share of its reporting to inflation compared to Sabah owned by the pro-government Kalyon Group. Cumhuriyet's reporting on inflation remains predominantly negative. In contrast, Sabah has a neutral to positive tone, even when the inflation rate increases rapidly in 2018. These trends show a clear example of the dual dynamics of pro-government media bias: minimizing the visibility of unfavorable economic indicators while simultaneously attempting to inject a positive narrative.

Figure A.9: Divergence in Inflation Coverage Frequency and Sentiment



Note: The figure shows the monthly proportion of news articles mentioning inflation in Cumhuriyet (orange line) and Sabah (blue line) plotted against the official annual inflation rate (dashed black line, right y-axis) between January 2017 and December 2019. The color of each marker represents the average sentiment score of the inflation-related articles in a given month, ranging from highly negative (dark red, -1.0) to positive (dark green, > 0.0). Inflation data is from TURKSTAT.

C Codebook for Sentiment Classification of Turkish Economic News

Task Overview

Your task is to read Turkish news articles and classify the economic sentiment of specific segments (chunks) of the text. You will read the article sequentially from beginning to end. While your evaluation will naturally be informed by the context of the full article, **you must assign a specific sentiment category to each individual chunk based on the information it contains.**

News media shapes public perception through two primary mechanisms:

1. **Selection:** Choosing to report positive or negative economic facts.
2. **Framing:** Using language to evaluate or frame an economic situation positively or negatively.

You must pay equal attention to both ***objective facts*** and ***subjective evaluations*** regarding the state of the Turkish economy.

The Four Categories

For each chunk, assign one of the following four categories:

Positive (1)

The chunk provides a positive evaluation OR reports a positive fact about the Turkish economy, its sectors, or domestic firms.

Positive Evaluation Example

Turkish: "2017'de 15 milyon euroluk yatırım yapmayı planlıyoruz." dedi. Colombini, Türkiye'de üretilen ilaçların Avrupa standartlarını yakaladığını kaydederek, bu başarıda Türk çalışanların büyük katkısı olduğunu bildirdi. Carlo Colombini, "Menarini Türkiye'ye inanıyor. Son yıllarda hakikaten önemli yatırımlar yaptık. Hem Türkiye'ye hem de Türkiye'deki fabrikaya yatırımımız büyüyerek devam edecek." diye konuştu.

English: "We plan to invest 15 million euros in 2017," he said. Noting that drugs produced in Turkey have reached European standards, Colombini stated that Turkish employees made a great contribution to this success... "Menarini believes in Turkey. We have made truly important investments in recent years. Our investment in both Turkey and the factory in Turkey will continue to grow," he said.

Explanation: A clear, straightforward positive evaluation showing high corporate confidence and ongoing foreign direct investment in Turkey.

Positive Fact Example

Turkish: "TÜİK'e göre milli gelirimiz 2016 boyunca yüzde 2.9 (son çeyrekte de yüzde 3.5) artış göstermiş. Bilindiği üzere 'milli gelir' bir ekonomide üretilmiş bulunan mal ve hizmetlerin yıllık değerini gösteriyor. Buna göre Türkiye 2016'da 2 trilyon 590 milyarlık 'üretim' gerçekleştirmiş."

English: "According to TURKSTAT, our national income increased by 2.9% throughout 2016 (and 3.5% in the last quarter). As it is known, 'national income' shows the annual value of goods and services produced in an economy. Accordingly, Turkey realized a 'production' of 2 trillion 590 billion in 2016."

Explanation: Reports an objective, highly positive macroeconomic fact (GDP growth) via journalistic selection.

Negative (-1)

The chunk provides a negative evaluation OR reports a negative fact about the Turkish economy, its sectors, or domestic firms.

Negative Evaluation Example

Turkish: "Türkiye'nin bu yıl dış borç ödemesi tutarı 215 milyar dolar. İhracatın ithalatı karşılama oranı rekor düzeyde düşüşte. Dış finansmanla yapılan dev projelerin geri ödemeleri başladı ve giderek artacak."

English: "Turkey's foreign debt payment amount this year is 215 billion dollars. The ratio of exports meeting imports is at a record low. Repayments of giant projects built with foreign financing have begun and will gradually increase."

Explanation: A highly critical, straightforward negative evaluation of structural flaws in the Turkish economy (debt burden and trade deficit).

Negative Fact Example

Turkish: "Otomotiv Distribütörleri Derneği'ne (ODD) göre, Türkiye'de bu yılın ocak-temmuz aylarında 88 bin 188 hafif ticari araç satışı yapıldı. Geçen yılın aynı döneminde 115 bin 147 hafif ticari araç satışı yapılmıştı. Bu yıl başından beri her ay küçülme yaşayan hafif ticari araç pazarı, ocakta yüzde 12, şubatta yüzde 10, martta yüzde 9, nisanda yüzde 11, mayısta yüzde 21, haziranda yüzde 44 ve temmuzda yüzde 46 daraldı."

English: "According to the Automotive Distributors Association (ODD), 88,188 light commercial vehicles were sold in Turkey in the January-July period of this year. In the same period last year, 115,147 light commercial vehicles were sold. The light commercial vehicle market, which has been shrinking every month since the beginning of this year, contracted by 12% in January... 44% in June and 46% in July."

Explanation: Reports an objective, undeniably negative economic fact regarding a severe contraction in a domestic industry.

Neutral (0)

The chunk is definitively about the Turkish economy, but it is purely descriptive, lacks a clear positive/negative direction, or presents perfectly balanced/mixed news.

Neutral Example

Turkish: "Çalışma Genel Müdürü Nurcan Önder başkanlığında toplanacak komisyonda, işçi tarafını Türkiye İşçi Sendikaları Konfederasyonu (TÜRK-İŞ), işveren tarafını ise Türkiye İşveren Sendikaları Konfederasyonu (TİSK) temsil edecek. Toplantıda, Kalkınma Bakanlığı, Hazine Müsteşarlığı ve Türkiye İstatistik Kurumu (TÜİK) uzmanları ülke ekonomisiyle ilgili verileri komisyon ile paylaşacak."

English: "In the commission to convene under the chairmanship of General Director of Labor Nurcan Önder, the worker side will be represented by TÜRK-İŞ, and the employer side will be represented by TİSK. At the meeting, experts from the Ministry of Development, Undersecretariat of Treasury, and TURKSTAT will share data regarding the country's economy with the commission."

Explanation: It is explicitly about domestic economic administration (minimum wage/labor boards), but the text is purely descriptive with zero polarity.

NA (Not Applicable)

The chunk is not informative regarding the Turkish economy. It may be about non-economic topics (sports, pure politics, culture) with **no economic relevance** or strictly about foreign economies with **no link to Turkey**.

NA Non-Economic Example

Turkish: "Amiklioğlu'nun cenazesi bugün saat 11.30'da TBMM'de yapılacak resmi törenin ardından, Bilkent Ahmet Akseki Camii'nde kılınacak öğle namazını müteakip İncek Mezarlığında toprağa verilecek. Amiklioğlu evli ve 2 çocuk babasıydı."

English: "Following the official ceremony to be held at the Parliament today at 11:30, Amiklioğlu's funeral will be buried at İncek Cemetery after the noon prayer at Bilkent Ahmet Akseki Mosque. Amiklioğlu was married and a father of two."

Explanation: Focuses purely on a funeral/event with absolutely no economic context.

Not NA Example: Tourism/Culture with Economic Relevance

Turkish: Ziyaretçilere kent rehberi, broşür ve kitapçıklar dağıtıldı... Türkiye'nin turizm sektöründeki en önemli buluşmalarından biri olan Travel Turkey İzmir Fuarı'nda Karşıyaka'yı en iyi şekilde tanıttıklarını ifade eden Belediye Başkanı Dr. Cemil Tugay "Türkiye başta olmak üzere dünyanın çeşitli yerlerinden gelecek sektör profesyonellerine ve ziyaretçilere ülkemizin aydınlık yüzü, Ege'nin ve İzmir'in incisi Karşıyamızı tüm güzellikleriyle anlattık." dedi.

English: City guides, brochures, and booklets were distributed to visitors... Stating that they promoted Karşıyaka in the best way at the Travel Turkey Izmir Fair, one of the most important meetings of Turkey's tourism sector, Mayor Dr. Cemil Tugay said, "We explained Karşıyaka... to sector professionals and visitors coming from various parts of the world, especially Turkey.""

Explanation: This text can seem to be about a local PR or lifestyle event, but it is framed in reference to Turkey's tourism sector attracting domestic and international visitors. It is a positive economic indicator. Code as **Positive (1)**.

Core Rules & Guidelines

Economic Ground Truths (Macro and Micro/Firm-Level)

You will read news articles which can be about Turkish economy at any level. They can cover macroeconomic trends or firm specific indicators. **When coding micro-level news, do not consider its macro-level impact or relevance.** A positive (negative) fact for a single domestic firm, sector, or consumer should be coded as positive (negative) for its own sake, regardless of its macroeconomic impact. Common economic indicators covered in news articles are listed below.

Macro-Level Indicators:

- *Negative:* Rising inflation, depreciating Turkish Lira (TL), widening current account deficit, rising unemployment, shrinking GDP, credit downgrades.
- *Positive:* Export growth, GDP growth, lowering inflation, increasing foreign direct investment (FDI), Lira gaining value.
- **Rule:** Global economic news should be coded on the basis of their relevance to or impacts on the Turkish economy.

Firm/Sector-Level Indicators:

- *Negative:* A domestic company declaring bankruptcy, reporting losses, laying off workers, or a sector facing supply chain crises.
- *Positive:* A domestic company opening a new factory, increasing profits, hiring workers, or expanding exports.
- **Rule 1:** Do not dismiss a firm's positive (negative) news just because the firm is "too small to affect the overall economy." Code it as positive (negative).
- **Rule 2:** News about global companies and brands should be coded on the basis of their relevance to or impacts on the Turkish economy.

Positive Firm/Sector Example 1 (Large Scale/Export)

Turkish: "Cengiz Eroldu, bu yıl iç pazarda 40 bin adet civarında Fiat Egea satışı hedeflediklerini de sözlerine ekledi. İhracat şampiyonu Ford... Türkiye ihracatının 11 yıldan bu yana kesintisiz lideri olan otomotiv sektörünün 2016 ihracat şampiyonları açıklandı. Uludağ Otomotiv Endüstrisi İhracatçıları Birliği (OİB), geçen yıl en çok ihracat gerçekleştiren firmalar sıralamasında zirvede Ford Otomotiv'in aldığını, ikinci sırayı bir önceki yıla göre bir basamak yükselen Tofaş'ın ve üçüncü sırayı Oyak Renault'un aldığını bildirdi."

English: "Cengiz Eroldu added that they target sales of around 40 thousand Fiat Egeas in the domestic market this year. The 2016 export champions of the automotive sector... have been announced. The Uludağ Automotive Industry Exporters Association (OİB) reported that Ford Otomotiv took the top spot in the ranking of companies with the highest exports last year, followed by Tofaş... and Oyak Renault in third place."

Explanation: Reports concrete achievements such as export champions and sector-based sales targets.

Critical Note: This content is **NOT NA** although the brands are global (Ford, Fiat, Renault). The news directly covers their production partnerships in Turkey and Turkey's export data. Because it presents positive data regarding the Turkish automotive sector, it must be coded as **Positive (1)**.

Positive Firm/Sector Example 2 (Small Scale/Entrepreneurship)

Turkish: "Otel ve hastanelerden gelen tek kullanımlık terlik siparişine yetişemeyen Yergök, 2 sene önce 280 metrekarelik atölyeye taşındı. 13 kişilik ekiple Türkiye'deki çoğu otel ve hastaneye günde 7 bin, aylık ise ortalama 150 bin 'kullanat terlik' üreten kadın girişimcinin şimdiki hedefi ise yurt dışına açılmak."

English: "Running at full throttle to keep up with disposable slipper orders coming from hotels and hos- pitals, Yergök moved to a 280-square-meter workshop 2 years ago. Producing 7 thousand 'disposable slippers' a day... the female entrepreneur's current goal is to expand abroad."

Explanation: A clear, unambiguous example of a domestic firm/entrepreneur expanding production capacity and targeting exports. Code as **Positive (1)**.

Negative Firm/Sector Example

Turkish: "Alacaklı konumdaki bir banka, aldığı ihtiyati haciz kararı sonrası Fişek Group'un merkez binasında 4 TIR dolusu mal haczetti."

English: "A creditor bank confiscated 4 truckloads of goods at the headquarters of Fişek Group following a precautionary confiscation decision it obtained."

Explanation: The news is restricted to a single domestic firm facing bankruptcy, asset seizure, and financial distress. It is a negative economic reality. Code as **Negative (-1)**.

Resolving the "Neutral" vs. "NA" Confusion (Scope of Turkey)

It is critical not to use "Neutral" and "NA" interchangeably.

- **Neutral** means the text *is* about the domestic economy, but it lacks polarity.
- **NA** means the text contains *no* domestic economic information.
- **The "Scope of Turkey" Rule:** Global economic events (e.g., US Federal Reserve decisions, European energy crises) are coded as **NA** *unless* the chunk (or the immediate

context) explicitly or implicitly links that event to an outcome for the Turkish economy. If a link to Turkey is established, score it based on the impact on Turkey.

NA Global Economy Example

Turkish: "AB (28) ve EFTA ülkeleri toplamına göre 2017 yılı Eylül ayında geçen yılın aynı ayına göre en fazla düşüş yüzde 22,2 ile Danimarka'da, yüzde 20,8 ile Letonya'da, yüzde 17,0 ile İrlanda'da görüldü."

English: "According to the EU (28) and EFTA countries total, the highest decrease in September 2017 compared to the same month of the previous year was seen in Denmark with 22.2%, Latvia with 20.8%, and Ireland with 17.0%."

Explanation: Focuses purely on foreign economic statistics with no mention of Turkey. Code as **NA**.

Linked Global Economy (Negative) Example

Turkish: "Tüm dünya iklim değişikliği ile mücadelede fosil yakıtlardan çıkışın önemini fark ederek adımlar atmaya başlamışken Türkiye'de 10'u ithal kömüre dayalı üretim yapan 26 kömür yakıtlı termik santral bulunuyor."

English: "While the whole world has started taking steps realizing the importance of exiting fossil fuels to combat climate change, there are 26 coal-fired thermal power plants in Turkey, 10 of which rely on imported coal."

Explanation: Links a global macroeconomic trend (energy shifts) directly to a negative structural dependency/flaw in the Turkish economy. Code as **Negative (-1)**.

Contextual but Chunk-Specific Coding

You will read the news articles from beginning to end, just as a standard reader would. You will know the context of the article and the story being covered. For instance, if Chunk 2 says, "This policy has an impact on our purchasing power," you will know what "this policy" is from Chunk 1. However, **your assigned score must reflect the specific chunk you**

are currently coding.

- Do not code a purely descriptive chunk as "Negative" just because the rest of the article is highly negative.
- A positive chunk can be followed by a negative chunk, or vice versa, as a news article evaluates an event from different perspectives.

Article-Level Task (The "All-NA" Exception)

In some cases, an entire article may be pulled into the data set, but contains no coverage regarding the Turkish economy (e.g., a purely political debate or a foreign economic event).

- If **every single chunk** in an article receives an **NA** score, fill out the separate "Article-Level Coding".
- When completing the article-level task, select **one or two of the options that apply to all chunks of the article**: (1) *"not about Turkey"* and (2) *"not about economy"*.
- This only applies if an article is 100% NA. Otherwise, you do not need to complete the article-level task.