

DISCUSSION PAPER SERIES

No. 10094

MEDIA POWER

Andrea Prat

*INDUSTRIAL ORGANIZATION and
PUBLIC POLICY*



Centre for Economic Policy Research

www.cepr.org

Available online at:

www.cepr.org/pubs/dps/DP10094.php

MEDIA POWER

Andrea Prat, Columbia University and CEPR

Discussion Paper No. 10094
August 2014

Centre for Economic Policy Research
77 Bastwick Street, London EC1V 3PZ, UK
Tel: (44 20) 7183 8801, Fax: (44 20) 7183 8820
Email: cepr@cepr.org, Website: www.cepr.org

This Discussion Paper is issued under the auspices of the Centre's research programme in **INDUSTRIAL ORGANIZATION and PUBLIC POLICY**. Any opinions expressed here are those of the author(s) and not those of the Centre for Economic Policy Research. Research disseminated by CEPR may include views on policy, but the Centre itself takes no institutional policy positions.

The Centre for Economic Policy Research was established in 1983 as an educational charity, to promote independent analysis and public discussion of open economies and the relations among them. It is pluralist and non-partisan, bringing economic research to bear on the analysis of medium- and long-run policy questions.

These Discussion Papers often represent preliminary or incomplete work, circulated to encourage discussion and comment. Citation and use of such a paper should take account of its provisional character.

Copyright: Andrea Prat

CEPR Discussion Paper No. 10094

August 2014

ABSTRACT

Media Power*

How much influence can news providers exert on the political process? This paper defines the power of a media organization as its ability to induce voters to make electoral decisions they would not make if reporting were unbiased. While existing media concentration measures are built by aggregating market shares across platforms, the new measure performs cross-platform aggregation at the level of individual voters on the basis of their attention shares. The paper derives a robust upper bound to media power over a range of assumptions on the beliefs and attention patterns of voters.

Computing the value of the index for all major news sources in the United States from 2000 to 2012 results in four findings. First, it cannot be excluded that the three largest media conglomerates could individually swing the outcome of most presidential elections. Second, in all specifications the most powerful media organizations are broadcasters: the press and new media are always below. Third, relative media power is well approximated by a simple function of attention shares. Fourth, a calibrated version of the model indicates that media power is much lower than the upper bound but still substantial

JEL Classification: L82

Keywords: media concentration and media plurality

Andrea Prat
Graduate School of Business
Columbia University
3022 Broadway
624 Uris Hall
New York, NY 10027-6902
USA

Email: andrea.prat@columbia.edu

For further Discussion Papers by this author see:
www.cepr.org/pubs/new-dps/dplist.asp?authorid=138721

*This project developed from discussions with Mark Armstrong. I am greatly indebted to him. I am also thankful to Sylvain Chassang, Matt Gentzkow, Lisa George, Kei Kawai, Leslie Marx, Eli Noam, Simon Wilkie, and seminar participants at Columbia, Harvard, Princeton, the New York City Media Seminar, and the 2014 North American Winter Meetings of the Econometric Society for helpful suggestions. Eric Hardy provided outstanding research assistance.

Submitted 27 July 2014

Media Power

Andrea Prat
Columbia University*

July 24, 2014

Abstract

How much influence can news providers exert on the political process? This paper defines the power of a media organization as its ability to induce voters to make electoral decisions they would not make if reporting were unbiased. While existing media concentration measures are built by aggregating market shares across platforms, the new measure performs cross-platform aggregation at the level of individual voters on the basis of their attention shares. The paper derives a robust upper bound to media power over a range of assumptions on the beliefs and attention patterns of voters.

Computing the value of the index for all major news sources in the United States from 2000 to 2012 results in four findings. First, it cannot be excluded that the three largest media conglomerates could individually swing the outcome of most presidential elections. Second, in all specifications the most powerful media organizations are broadcasters: the press and new media are always below. Third, relative media power is well approximated by a simple function of attention shares. Fourth, a calibrated version of the model indicates that media power is much lower than the upper bound but still substantial.

1 Introduction

Defining and Measuring Media Power The media industry plays a crucial role in keeping government accountable. Most of the information that we as citizens

*This project developed from discussions with Mark Armstrong. I am greatly indebted to him. I am also thankful to Sylvain Chassang, Matt Gentzkow, Lisa George, Kei Kawai, Leslie Marx, Eli Noam, Simon Wilkie, and seminar participants at Columbia, Harvard, Princeton, the New York City Media Seminar, and the 2014 North American Winter Meetings of the Econometric Society for helpful suggestions. Eric Hardy provided outstanding research assistance.

have about our political leaders comes from the media. Powerful media owners can attempt to manipulate information for their own goals. William Randolph Hearst, the owner of the *Morning Journal* and the source of inspiration for Orson Welles' *Citizen Kane*, inflamed the American public opinion against Spain through highly biased coverage of the Cuban Rebellion. Hearst's propaganda is cited as a key cause of the Spanish-American War of 1898. Perhaps, the most chilling quote on this topic is found in Adolf Hitler's *Mein Kampf*: "By the skillful and sustained use of propaganda, one can make a people see even heaven as hell or an extremely wretched life as paradise." It is no surprise that the issue of media power has occupied for many decades a central position in public policy debate.

While the debate is often vehement, effective policy discussion is hampered by the lack of a widely accepted definition of what constitutes a dangerously high level of media concentration. Depending on the measure adopted, conclusions can be polar opposites. For instance, a simple application of the Hirschmann-Herfindahl Index reveal that most US media industries have low levels of concentration: the HHI of radio, tv stations, and the daily press are respectively 545, 253, and 191 (Noam 2009) and the Department of Justice classifies industries with an HHI lower than 1500 as unconcentrated. Yet, a canonical reference in this area (Bagdikian 2004) uses market share measures to argue that the US media industry is dominated by five companies, whose "concentrated influence exercises political and cultural forces reminiscent of the royal decrees of monarchs rejected by the revolutionists of 1776". Disagreement is not just about levels but also about whether concentration is increasing or decreasing, with optimists celebrating the development of new media and pessimists pointing at waves of media mergers.

As Polo (2005) points out, existing competition policy provisions do not fully address concerns about media concentration. Standard indices, such as Herfindahl, measure the *direct* effect of media concentration on consumer welfare. However, the media industry is different from other industries in that it has an indirect effect on welfare through information externalities imposed on the policy process. Concentration is damaging not only because it raises prices and reduces quantities but also because owners may be able to manipulate democratic decision-making in a way that inflicts damage on citizens through an indirect channels – and the latter is typically a much greater concern. Antitrust provisions must be complemented by media-specific considerations (Ofcom 2009).¹

¹Political influence is only one of the possible media-specific welfare effects that are not covered by standard competition policy. Anderson and Coate (2005) provide a theoretical analysis of market failure in broadcasting. George and Waldfogel (2003) document how the media industry structure is shaped by preference externalities, leading to products that are more likely to cater to larger

The problem is not the choice of a particular index – like the Herfindahl Index – but the definition of the relevant market. If we use a standard notion based on demand, we will tend to define media markets in terms of platforms: radio, newspapers, tv, internet, etc.² However, a platform-based definition is at the same time too narrow and too broad. It is too narrow, because what matters from the point of view of democracy is whether citizens are informed, not whether they get their news from ink and paper, a television screen, or their mobile phone. It is also too broad, because not all media sources on a platform produce information. This problem is particularly severe for radio, television, and digital media, where news covers a small share of the platform content. In other words, if we are interested in understanding where voters obtain their political information, we have to go beyond the standard notion of market shares.

Partly in response to this perceived challenge, in 2003 the US Federal Communications Commission attempted to introduce a cross-platform measure: the Media Diversity Index. The index assigned a weight to every platform: broadcast TV (33.8%), newspapers (20.2%), weekly periodicals (8.6%), radio (24.9%), cable internet (2.3%), all other internet (10.2%). Within each platform, every outlet was given equal weight. The index generated controversy both because of how it assigned weights within a platform and for how it aggregated them across platforms. It was eventually struck down by an appellate court in *Prometheus Radio Project v. FCC* because of “irrational assumptions and inconsistencies.”

Methodology As the court’s decision underscores, it would be useful to discuss media concentration on the basis of a theoretical framework. However, such framework faces two challenges. First, while it is clear that any meaningful media index must aggregate information within and across platforms, it is not clear how to perform such aggregation. Second, even if we focus on just one platform, the damage that a media organization can inflict on citizens depends on how citizens would react to an attempt by said organization to condition the democratic process. However, this is a difficult question to answer before the attempt actually occurs. The evidence on the effect of media bias on citizens points in different directions and at this stage no general set of predictions that can be used as a robust basis for a model of media

groups. Also, the media can influence welfare through changes in social behavior (La Ferrara et al 2012). This paper focuses exclusively on the welfare effect due to influence on the political process.

²For instance, an international review of 14 countries and the European Union (OECD 1999) found that that: “in no case was it indicated that a market definition was adopted in which broadcasting and other forms of media were held to be sufficiently substitutable as to be in the same market from the perspective of consumers.”

influence (see literature review below).

This paper suggests a theoretical approach to address these two issues. To deal with the first challenge, the paper moves away from the two-stage approach employed by the FCC's Media Diversity Index, as well as all other existing media measures, which consists of first analyzing concentration for individual media platforms and then aggregating across platforms.. The most basic unit of analysis is not a particular media market but the mind of individual voters. For every voter, we can conceivably analyze the influence of news sources on his information and hence his voting decisions. This leads to a natural way of aggregating power at the individual level across platforms. Once we determine the influence that a news source has on each voter, we can derive its overall influence by aggregating across voters, thus determining the vote share it controls. In other words, while existing measures aggregate first over people and then over platforms, we proceed in the opposite order. This takes care of the problem highlighted above because the weight we give to individual news sources is individual-specific and it corresponds to their ability to influence that individual's political choices.

To respond to the second challenge – the indeterminacy of voters' reaction to media bias – the paper starts with a large set of possible assumptions over voters' beliefs and over their attention patterns and it characterizes the upper bound to media influence over the whole set of assumptions. The resulting power measure has a worst-case scenario flavor: it identifies the potential damage that a media organization can inflict on the democratic process.

The power of a media organization is defined as its ability to influence electoral outcomes through biased reporting. A powerful media mogul is one that can persuade voters to cast their ballot in favor of a candidate they would not elect if they had unbiased information. The power index is a continuous measure that represents the ability to swing elections: the more powerful the media organization, the worse the candidate it can get elected.

With this definition of media power, the most granular unit of analysis is the attention of the individual voter. Each voter can follow multiple news sources belonging to different platforms. The analysis begins by determining the influence that individual sources have on that voter. Influence on individual voters is then aggregated directly over the whole electorate, thus creating a platform-neutral index.

There are two possible ways to proceed to determine the influence of media over voters. If we had a model of how voters and media behave, we could analyze it to provide an exact measure of media influence. However, despite the considerable progress made by the empirical literature on the political economy of mass media (summarized below), some key factors are intrinsically difficult to observe, like the

motivations of media owners, the way voters update their political views based on information they receive from multiple sources, the number of news items that voters observe or recall, the ability of voters to detect an attempt to influence through news bias, the voters' willingness to switch away from biased sources. Yet, those factors are crucial in determining equilibrium influence.

This paper adopts a different approach, which is inspired by a recent applied literature on “robust bounds” in agency problem, like Chassang (2011), Madarasz and Prat (2011), Carroll (2013), and Chassang and Padro i Miquel (2013). A standard agency-theoretic problem assumes that the principal has a – possibly probabilistic – model of the agent’s preferences and constraints and derives precise predictions on agent behavior and optimal mechanisms. This literature instead considers a large set of possible agent models and, rather than deriving point estimates, it identifies bounds on the set of possible outcomes. For example, Chassang and Padro i Miquel (2013) study robust whistleblowing policies in a situation where the planner is unsure about the motives of agents. Rather than solving for optimal contracts in specific environments, she considers the effect on equilibrium corruption of possible policies under a continuum of environments. In particular, this leads to the identification of an upper bound to corruption and of a whistleblowing policy that guarantees a robust bound on maximal corruption. This paper develops an analogous methodology to find bounds over the influence of media organizations. It allows for a set of assumptions on voters and media owners and it determines the lower and upper bound on the influence that a particular media organization has over voting outcomes. As it is easy to identify a set of assumptions under which influence is zero, the paper will focus on characterizing maximal influence. Maximal influence will be expressed in terms of two sets of observable variables: media consumption patterns and media ownership structure.

Theory The theoretical contribution of the paper lies in the analysis of the upper bound to media power for the following set of assumptions. The analysis requires a known media consumption matrix, which describes what media sources individual voters currently follow. Voters are Bayesian and they use the information they receive from the media sources they follow to decide who to vote for. Voters have subjective and possibly incorrect beliefs on the probability that media are captured. They also have a potentially bounded capacity to absorb information (*bandwidth*): they only observe or remember a certain number of news items from the various sources they follow. The relative quality of political candidates is stochastic and the media receive a large number of signals correlated with candidate quality.

As the goal is to characterize maximal influence, the analysis focuses on a media

owner who is assumed to have a pure political motive: he wants a particular candidate to win this election, and he has no concerns for the short- and long-term commercial return or the journalistic reputation of the media companies he owns.

While, for a generic set of parameters, the equilibrium of this game requires solving a difficult fixed-point problem, it turns out that the worst-case scenario can be expressed as the solution of a polynomial equation. As one would expect, the worst case corresponds to a naive electorate who cannot undo media bias. However, the role of attention patterns is more subtle. The worst case is not necessarily the one where voters have uniform minimal bandwidth.

The paper therefore proceeds to characterize the worst-case scenario, where bandwidth is allowed to vary across voters. It is shown that for each segment the worst case involves either minimal or maximal bandwidth and a formula to compute the index is obtained.

The limit of the analysis is clear: as results take the form of sets, not points, it makes no predictions about media power within the lower bound and the upper bound. Media owners may be less ‘evil’ – or just more profit-driven – and voters may be less naive or their attention patterns may be less conducive to media influence. The present contribution lies in identifying the maximal level of influence that the media can exert on the political process on the basis of a set of conceivable assumptions about voters and owners. If the media regulator has a prior belief on how voters and owners behave, then this worst-case exercise can be skipped. If instead (as it is the case in reality) there is unmodeled uncertainty on all these factors, then an upper bound approach has some value.

Empirics A key feature of the power index developed here is that it can be computed with existing US media consumption data. The empirical part of the paper reports two sets of results: (1) The computation of the upper bounds to media power; and (2) A calibration exercise based on Della Vigna and Kaplan’s (2007) estimates of Fox News’ influence.

For the upper bounds, values of the power index are computed for all major US media organizations from 2000 to 2012 on the basis of data contained in the biennial Media Consumption Survey conducted by the Pew Research Centers. The scope of the survey has grown over the years: in 2010 and 2012, the survey covers the daily press, weekly and monthly magazines, television news, and websites.

The paper reports the media power of individual news sources as well as media conglomerates that own multiple sources. The computed values indicate that the three most powerful US media organizations in 2012 were, in order of decreasing power, News Corp (the ultimate owner of Fox TV and the Wall Street Journal),

Comcast (NBC and MSNBC), and Time Warner (CNN, Time Magazine, and HBO). The most powerful newspaper, the New York Times, is in tenth position behind the most powerful pure-internet source, Yahoo News, in sixth position. NPR is in fifth position.

The robustness of the index is probed along various directions: different criteria for inclusions of news sources (daily or weekly), different definitions of the index (worst case and minimal attention), different years (2010 and 2012, when all major media are included), and different assumptions on the distribution of voter ideology. The relative ranking of the major media organizations is highly stable across specifications.

For the calibration exercise, the paper relies on the midpoint of the estimates that Della Vigna and Kaplan (2007) obtained in the 2000 US Presidential election for Fox News, which is the single most powerful media source in the US according to the upper bounds estimates obtained here. Within the present model, Della Vigna and Kaplan's estimate yields a value of the degree of naivete of voters that can be used to compute the media power of all major media organizations. The magnitude of the media power is about one tenth of the upper bound computed above, while the relative ranking is similar. Based on the vote share distribution in the past 50 years, the estimate implies that News Corp has a 13% probability of being able to swing the outcome of a Presidential election on its own.

Policy Implications The theoretical and empirical analyses yield four (highly tentative) implications for media regulation.

First, despite the fact that standard concentration measures are not particularly high in any media industry (Noam 2009), the upper bounds to media power obtained in this paper are large. In the minimal bandwidth case, News Corp could control elections with a vote share difference of 22 percentage points, which is more than almost all US presidential elections. The equivalent figure for Comcast and Time Warner is respectively 15% and 12%. The numbers are larger if one looks at the worst-case scenario index. Of course, being an upper bound result, this finding does not mean that media conglomerates *will* exert this large influence. However, it indicates that, given the observed media consumption patterns, there are conceivable circumstances under which those media groups can wield this kind of power.

The size of these upper bounds supports the criticism – discussed above – of the standard approach to measuring media concentration. The problem is that, while most US media industries appear relatively competitive according to standard market-based definitions, this does not translate into individual-level media plurality: a large share of the electorate get their political information from a small number

of news sources, typically television networks. The proposed index, which documents this form of media concentration, highlights the need for media regulators to complement standard market-centered concentration measures with a voter-centered approach.

Second, while the absolute values of the power index vary with the specification chosen, the relative ranking of media organizations is quite stable. Whether one uses any of the upper bounds or the Della Vigna and Kaplan calibration, the four most powerful media organizations are mainly television companies. The power of the press and new media is more limited, and comparable to that of public radio. Despite the increasing role of new media (George 2008), ownership of television networks continues to be the major issue in the debate on media regulation in the United States.

Third, a consequence of the stability of relative rankings across all empirical specifications is that, for the purpose of comparison, one can focus on the simplest form of the power index, namely minimal bandwidth. In that case, the power of a media organization G is simply proportional to

$$\frac{a_G}{1 - a_G},$$

where a_G is G 's *attention share*. (the attention share of a news source for one voter is one over the number of sources the voter follows; the attention share of G is the average attention share that G 's sources command across all voters). Attention share is different from market share and it cannot be obtained by aggregating market shares. However, attention share can be easily computed on the basis of individual media usage information, such as the one used in this paper.

Fourth, as the calibration exercise shows, one can obtain point estimates of media power based on observed patterns. As the empirical literature on mass media provides more evidence on influence patterns, it will be possible to put more precise values on the parameters that govern voters' response to bias. In turn, this will lead to better predictions on the effect of mergers and other structural changes in the media industry.

The paper concludes with an illustration of how media power indices could be used to assess the risk of media mergers (with all the caveats discussed above). Unlike other measures, the power index applies in a consistent way to within-platform and across-platform mergers.

Related Literature The present paper relates to a large and growing body of empirical research on media bias and the influence of media on the democratic system.

The fact that media scrutiny influences both policy chosen by elected officials and electoral outcomes is amply documented (See Prat and Stromberg 2012 for a survey). The presence of news slant has been documented through partisan references (Groseclose and Milyo 2005), airtime (Durante and Knight 2006), space devoted to partisan issues (Puglisi 2006), and textual analysis (Gentzkow and Shapiro 2010). Evidence about the effect of media bias on electoral outcomes is mixed. Della Vigna and Kaplan (2007) find a significant effect of Fox News entry on US voting patterns and Enikolopov, Petrova and Zhuravskaya (2011) find an even stronger effect of the entry of NTV into selected Russian regions. However, Gentzkow et al (2011) rule out even moderate effects of entry and exit of partisan newspapers on party vote shares in the United States from 1869 to 2004. Moreover, there is also evidence that US newspaper readers show some sophistication in the way they handle media bias (Durante and Knight 2006, Chiang and Knight 2011). Evidence on the motivations of media owners is mixed too. Durante and Knight (2006) document sudden and significant changes in state television coverage in Italy when Silvio Berlusconi came to power. However, Gentzkow and Shapiro (2010) find that owner identity has no significant effect on newspaper slant in the US.

On the theory side, media bias can be modeled as coming from two sources. Even though the media have no vested interests, consumers may demand biased coverage (e.g Mullainathan and Shleifer (2005), Gentzkow and Shapiro (2006)). However, bias can also be supply-driven (Baron 2006, Besley and Prat 2006, Balan, De-Graba, and Wickelgren 2009, Duggan and Martinelli 2011, Anderson and McLaren 2012, Petrova 2012). The present model focuses on the second source of bias. Besley and Prat (2006) assume that the goal of news manipulation is to influence the electoral process and determine conditions – chiefly higher media concentration – under which the goal is more likely to be reached. Anderson and McLaren (2012) compare a media duopoly to a media monopoly, in the presence of politically motivated media owners, and analyze the effect of a merger. Brocas et al. (2010) characterize the effect of competition and ownership on diversity of viewpoint and informational efficiency. With respect to existing theories, this paper contains two methodological contributions: defining a media power index over a generic set of news sources and a generic media consumption matrix; and the use of the robust bound approach. Those in turn lead to the paper’s main substantive contribution: a measure of power that can be computed with existing media usage data.

As in the Bayesian persuasion literature (Kamenica and Gentzkow 2011, Gentzkow and Kamenica 2012), this paper proceeds by characterizing the set of possible distributions of the receiver’s beliefs that the sender can induce, and hence the possible distributions over outcomes. In the present model, there is a mass of heterogeneous

receivers who get signals from different sources and the relevant outcome is the identity of the election winner. The sender, the media owner, chooses a reporting strategy in order to maximize the chance that her preferred candidate is elected. One noteworthy difference with Kamenica and Gentzkow (2011) is that in the present model there are a large number of reportable signals and receivers have limited bandwidth: individuals observe only a small subset of the reported signals and they are unaware of the number of signals that individual media sources report. This assumption, which is in the spirit of studying the worst-case scenario, affords the sender the ability to undertake selective reporting in a covert manner. Media power would be lower if voters observed the number of signals reported.³

The next section describes the model and characterizes the benchmark case where all media outlets are unbiased. Section 3 introduces an evil owner and studies power when the voter bandwidth is known. Section 4 derives the worst-case power index. Section 5 contains the empirical analysis. Section 6 concludes by mentioning policy implications.

2 Unbiased Media

Let us begin by stating and analyzing the model under the assumption that all news sources are unbiased.

There are two candidates, A and B . The relative quality of candidate B over candidate A is a random variable σ , distributed according to density function f with support $[0, 1]$. The function f is symmetric around $\frac{1}{2}$ ($f(\sigma) = f(1 - \sigma)$) and unimodal. There is a mass one of voters, who for now have homogenous preferences.⁴ In expectation, the two candidates are equally attractive, but given σ voters prefer candidate B if and only if $\sigma \geq \frac{1}{2}$. Specifically, voters' payoff is $\frac{1}{2}$ if they elect A and σ if they elect B .

³The same set of assumptions that make our worst-case scenario worse also make our best-case scenario weakly better. Our senders have no influence when voters are completely aware of media owners' motives because the fact that signals can be covertly selected means voters disregard information coming from biased media. Unless the media organization controls all news sources, the lower bound of its power index is zero.

⁴The extension to heterogeneous preferences is discussed at the end of Section 4 as well as in the empirical analysis in Section 5, where we shall divide voters into Democrats, Republicans, and independents. In our setting, the pre-existing opinion of a voter can be modeled as signals that the voter received before the current electoral campaign started. The whole analysis can be performed with heterogeneous preferences, but to keep the exposition simpler, we focus mainly on homogeneous preferences.

However, voters do not observe the relative quality σ directly. They rely on the media for information. There is a set of media outlets, who do not observe σ directly either but they receive binary signals drawn from a binomial distribution with mean σ . Let \mathbb{M} denote the finite set of media outlets, with typical individual outlet denoted $1 \leq m \leq |\mathbb{M}|$. Let $x_m = (x_{m1}, \dots, x_{mN})$ denote a vector of N binary signals – *news items* – observed by outlet m , with $\Pr(x_{mi} = 1|\sigma) = \sigma$. News items are, conditional on σ , independent within and across media outlets.

In general voters may follow more than one outlet. Let $M \subset \mathbb{M}$ denote some subset of outlets. Then voters are partitioned into *segments*, indexed by the subset M of outlets they consume, and for each $M \subset \mathbb{M}$ let q_M be the fraction of voters who consume (exactly) the subset M . Clearly

$$\sum_{M \subset \mathbb{M}} q_M = 1 .$$

For simplicity, suppose that all voters see at least one outlet, so that $q_\emptyset = 0$. This makes no difference provided that voters who receive no messages vote randomly.

Table 1 depicts a possible media consumption matrix. Voters belong to ten possible segments. each of which contains 10% of the total population. There are seven media outlets: two television channels (Tv1 and Tv2), three newspapers (Np1, Np2, Np3), and two news websites (Web1 and Web2). A solid square in a cell indicates that voters in the corresponding row follow the news source in the corresponding column. The table reports two possible measures of an outlet’s penetration: the reach (the total share of voters who follow that source) and the attention share. The latter is defined as follow: for each segment, let m ’s attention share be zero if voters in that segment do not follow m and $1/\#M$ if they do (where $\#M$ is the number of outlets followed in that segment); m ’s aggregate attention share is the weighted

average of m 's attention share in each segment.

Segment	Share	Tv1	Tv2	Np1	Np2	Np3	Web1	Web2
1	10%	■						
2	10%	■						
3	10%	■		■				
4	10%			■				
5	10%		■					■
6	10%		■		■		■	■
7	10%		■		■		■	
8	10%		■			■	■	
9	10%					■	■	■
10	10%				■	■	■	■
Reach		30%	40%	20%	30%	30%	50%	40%
Attention		25%	14.1%	15%	8.3%	9.1%	15%	13.3%

Table 1: Example of a media consumption matrix

Unbiased media simply report all the N signals they receive. Thus outlet m reports N binary numbers. A voter in group M is exposed to $|M|N$ signals.

However, voters have potentially limited *bandwidth*. Voters in segment M observe or remember a limited number $K_M \in \{1, \dots, N\}$ of news items, randomly selected among the set of $|M|N$ items available. The assumption that all voters within segment M have the same bandwidth is without loss of generality as segments with heterogeneous bandwidth can be subdivided into homogenous ones. Bandwidth plays no role in the unbiased case, but will be crucial once media can be biased.

A voter i in segment M observes $|M|K$ binary news items and computes their average s^i . As all binary signals are independent, s^i is the best unbiased estimator of σ , given the voter's information. Voter i prefers B if $E[\sigma] \geq \frac{1}{2}$. Under sincere voting, he casts his ballot for B if and only if $s^i \geq \frac{1}{2}$.

What is the probability that voter i in M votes for B ? Let s_m be the average of the N signals received by outlet m . If N is finite, s_m may be different from σ , meaning that the unbiased source m can report a biased vector of signals simply because it makes a mistake. As we are not interested in situations where voters make errors because of unbiased but inaccurate reporting, assume that the number of signals that each outlet receives is very large. With $N \rightarrow \infty$, we have $s_m \rightarrow \sigma$ for all media m . In that case, the probability that voter i in M votes for B is equal to the probability that the sample mean of a binomial random variable with $|M|K$ realizations and mean σ is at least $1/2$. By the law of large numbers this probability

is also the vote share within segment M . Thus the vote share in segment M is at least $1/2$ if and only if σ is at least $1/2$. As this holds for every segment, we have verified that:

Proposition 1 *With unbiased media, as $N \rightarrow \infty$, B is elected if and only if $\sigma \geq \frac{1}{2}$.*

While the identity of the winning candidate in Proposition 1 is unaffected by assumptions on voter bandwidth, the margin of victory is affected by bandwidth – a fact that will play a crucial role in the next section. To illustrate this point, Figure 1 depicts the vote share of Candidate A as a function of candidate quality differential σ for four possible level of bandwidth, from the smallest: $K_M = 1$ to the limit as $K_M \rightarrow \infty$.

As one expects, the vote share (of A) is decreasing in the quality (of B). Independent of bandwidth, vote share is exactly $1/2$ when $\sigma = 1/2$, as predicted in Proposition 1. However, bandwidth determines the slope of the vote share function. The probability that a voter chooses the wrong candidate, say A when $\sigma > \frac{1}{2}$, corresponds to the chance that he observes/recalls a higher number of signals favorable to A than to B . That decreases with K_M and in the limit it goes to zero. This explains why the vote share function becomes increasingly S-shaped as bandwidth increases.

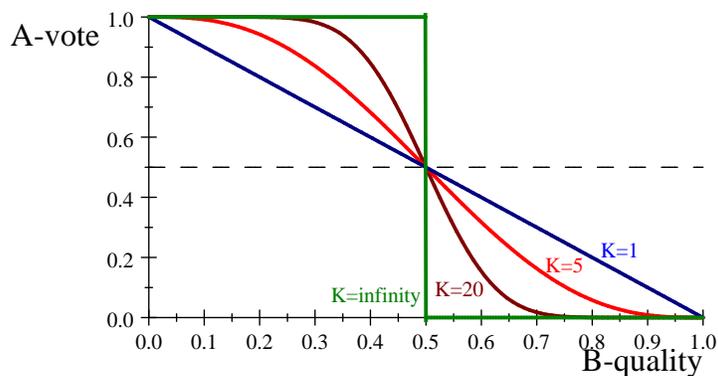


Figure 1: A 's vote share in segment as a function of quality σ

3 Power Under Biased Media with Known Bandwidth

Let us now entertain the possibility that an agent acquires control of a subset G of the set of active media \mathbb{M} . In the worst-scenario spirit, this agent – henceforth known as the “evil media owner” – has one goal only: he wishes to see candidate A elected, independent of the relative quality of the two candidates. This excludes that the media owner might moderate his political bias because of commercial profit or journalistic integrity, but still allows for the possibility that he reports less biased news in order to bolster his ability to persuade voters. The goal of this section is to identify a set of conditions under which the evil media owner is successful in his attempt to get his candidate elected.

Let us introduce two measures of the importance of media group G . The *reach* of subset G , i.e., the fraction of voters who follow outlet m , is then

$$r_G = \sum_{M: M \cap G \neq \emptyset} q_M .$$

The *attention share* of media group G in segment M is defined as

$$g_M = \frac{|M \cap G|}{|M|} .$$

and let its overall attention share be

$$a_G = \sum_M q_M g_M .$$

While the reach is a standard measure, attention share does not appear to be used by either practitioners or scholars.

In the pessimistic view of the world that we must adopt to compute the upper bound to media influence, the evil owner faces no constraint to selective reporting. In particular, he can fail to report any or all the items that are favorable to B . Recall that each outlet receives an unboundedly large number of news items N . Hence, for any $\sigma \in (0, 1)$, the evil owner can find at least K items favorable to A . This means he can choose to report any share $s \in [0, 1]$ of news items that are favorable to B . In one extreme case $s = 1$ and all signals are reported, as in the unbiased case. In the other extreme $s = 0$ and only signals that are favorable to A are reported.

A voter with bandwidth K observes/recalls K of the items that the biased media outlet reports. In the worst-case spirit, the voter does not see how many items the outlet actually reported. If he did, he could deduce the presence of bias directly.

How do voters react to the possible presence of an evil media owner? Let $\beta \in (0, 1)$ be the prior probability that voters assign to the presence of an evil media owner. This is a subjective parameter that captures the voters' views on the possibility that G is under the effective control of a unitary owner and that such owner is in biased in favor of candidate A .

The parameter β should be viewed as a potentially incorrect belief rather than the objective probability that the owner is biased. In other words, voters may be gullible and not realize that a particular media organization is likely to be captured by an evil owner.

If we imposed the restriction that the belief is correct, we could define the worst case in the form $\min_{\beta} \beta \times [\text{damage given } \beta]$. Instead, with incorrect beliefs, the appropriate worst-case notion is simply $\min_{\beta} [\text{damage given } \beta]$. Assuming that voters' beliefs are correct would reduce, but not eliminate, media power. However, the available evidence on voters' beliefs is far from guaranteeing that voters' beliefs correspond to objective probabilities. Hence, a reasonable upper bound analysis must allow for the possibility that beliefs are incorrect.

Recall that a voter with bandwidth K_M in group M receives/remembers a K_M -sized vector of signal realizations randomly drawn from the media outlets in group M . As before, the number of signals that come from a particular outlet is random and the selection of signals within an outlet is random too. Now, however, the voter faces a more complex Bayesian updating process.

To analyze this, we begin by writing the probability that a voter in group M observes a particular realization of the K_M -sized signal vector y^i he receives from media outlets in M . The vector includes news items randomly drawn from outlets in M . Let y_k^i denote the k th realization of the vector and let $m(k)$ denote the media outlet it is drawn from.

This probability is computed according to the beliefs of the voter. Suppose the voter believes that the owner is evil with probability β and that an evil owner would use reporting strategy $\hat{\sigma}$. Then, the probability of realization $y^i = Y$ would be given by:

$$\begin{aligned} & \Pr(y^i = Y | \sigma, \hat{\sigma}) \\ &= \sigma^{N_1(M/G)} (1 - \sigma)^{N_0(M/G)} \left((1 - \beta) \sigma^{N_1(G)} (1 - \sigma)^{N_0(G)} + \beta (\hat{\sigma})^{N_1(G)} (1 - \hat{\sigma})^{N_0(G)} \right) \end{aligned}$$

where $N_y(M/G)$ is the number of signals with value y coming from unbiased outlets, while $N_y(G)$ is the same variable for potentially biased outlets.

The voter computes the expected value of candidate quality as follows:

$$E[\sigma|Y, \hat{s}] = \frac{\int_0^1 \Pr(y^i = Y|\sigma, \hat{s}) \sigma f(\sigma) d\sigma}{\int_0^1 \Pr(y^i = Y|\sigma, \hat{s}) f(\sigma) d\sigma}$$

and votes for A if and only if $E[\sigma|Y, \hat{s}] \leq \frac{1}{2}$.

We now compute a lower bound to posterior $E[\sigma|Y, \hat{s}]$.

Lemma 2 *For any vector of signals Y , let $N_1(M/G)$ be the number of positive signals from unbiased media, let $N_0(M/G)$ be the number of negative signals from unbiased media, and let K_G be the number of signals from biased media. The voter posterior $E[\sigma|Y, \hat{s}]$ is bounded below by*

$$\frac{\int_0^1 \sigma^{N_1(M/G)} (1 - \sigma)^{N_0(M/G) + K_G} \sigma f(\sigma) d\sigma}{\int_0^1 \sigma^{N_1(M/G)} (1 - \sigma)^{N_0(M/G) + K_G} df(\sigma) \sigma}.$$

Proof. See Appendix. ■

The lemma states that, given $N_0(M/G)$ and $N_1(M/G)$, the value of $E[\sigma|Y, \sigma]$ can never be lower than the value achieved when all the biased outlets' news items are favorable to A and the voter believes that all media are unbiased. At this stage, this bound should be interpreted in a strict mathematical sense: the value of $E[\sigma|Y, \hat{s}]$ can never be lower than the value of the bound.

Now, let us translate – again, in a purely mathematical sense – the lower bound on the posterior into an upper bound on the vote share that candidate A can receive. The lower bound in (1) is greater or equal to $\frac{1}{2}$ if and only if

$$N_1(M/G) \geq N_0(M/G) + K_G$$

In other words, the voter selects candidate B if and only if the number of signals in favor of Candidate A is weakly larger than the number of signals in favor of B , including signals from both unbiased and potentially biased outlets. The “weakly” part comes from the fact that $\beta > 0$. If the two candidates are supported by exactly the same number of signals, the voter would be exactly indifferent if $\beta = 0$. But for any strictly positive β , he must prefer B .

The probability that the voter selects B is thus equal to:

$$\Pr(N_1(M/G) \geq N_0(M/G) + K_G) = \Pr\left(\frac{N_1(M/G)}{N_1(M/G) + N_0(M/G) + K_G} \geq \frac{1}{2}\right)$$

The probability that an individual signal takes value 1 is $(1 - g_M)\sigma + g_M \cdot 0$. The probability that a particular voter selects A is given by the cumulative distribution

of a binomial with parameter $(1 - g_M)\sigma$, with K_M possible realizations, evaluated at the highest integer that is strictly smaller than $K_M/2$. For $K_M = 1$ it is 0, for $K_M = 2$ it is 0, for $K_M = 3$ it is 1, etc). Let $\lceil K_M/2 \rceil$ denote the ceiling of $K_M/2$, namely the smallest integral that is at least as large as $K_M/2$. Then:

$$p_A(g_M, K_M, \sigma) = \sum_{k=0}^{\lceil K_M/2 \rceil - 1} \binom{K_M}{k} ((1 - g_M)\sigma)^k (1 - (1 - g_M)\sigma)^{K_M - k}$$

By the law of large numbers, $p_A(g_M, K_M, \sigma)$ is the share of A votes in segment M .

We are now ready to move from a purely mathematical interpretation of the bound to its game-theoretic meaning. If $p_A(g_M, K_M, \sigma)$ is an upper bound to the vote share that A can achieve under any voter belief, this means that in equilibrium of game A 's vote share in M can be higher than $p_A(g_M, K_M, \sigma)$. Furthermore, we can easily see that this bound is tight by finding one particular set of beliefs that achieves the bound. To see this just assume that the evil owner uses a strategy of reporting only zeros. When $\beta \rightarrow 0$, it is easy to verify that the vote share in M does indeed tend to $p_A(g_M, K_M, \sigma)$ for any K_M .

We summarize the analysis so far with:

Proposition 3 *The upper bound to A 's vote share in a segment where G controls a share g_M of outlets and voters have bandwidth K_M is*

$$p_A(g_M, K_M, \sigma) = \sum_{k=0}^{\lceil K_M/2 \rceil - 1} \binom{K_M}{k} ((1 - g_M)\sigma)^k (1 - (1 - g_M)\sigma)^{K_M - k}$$

Let us re-visit figure 1, which depicted A 's vote share in a segment with only unbiased media. With our current notation, we would express that as $p_A(0, K_M, \sigma)$. Let us compare it with a segment where, say, 1/4 of the outlets are biased: Figure 2

now depicts $p_A\left(\frac{1}{4}, K_M, \sigma\right)$ for various values of K_M .

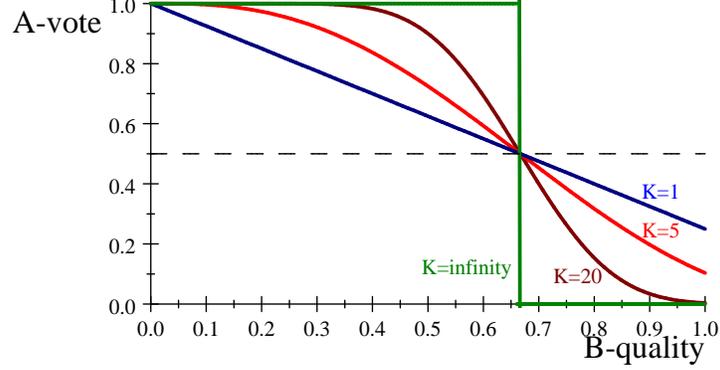


Figure 2: A 's vote share in segment as a function of quality σ

In Figure 2, A 's vote share is still a decreasing function of σ and it is more s-shaped as bandwidth increases. However, now the curves have all shifted to the right. Rather than intersecting the $1/2$ horizontal line at $\sigma = \frac{1}{2}$ as in the unbiased case, the intersection is now at $\sigma = \frac{2}{3}$. Media power is now visible: the evil owner can get a majority of voters in segment M to vote for A even when B is a superior candidate.

The cases where bandwidth is extreme – $K = 1$ or $K \rightarrow \infty$ – are particularly easy to characterize and will play a crucial role later on:

Corollary 4 (i) *When bandwidth is minimal, A 's vote share is a linear function of σ :*

$$p_A(g_M, 1, \sigma) = (1 - g_M)(1 - \sigma) + g_M;$$

(ii) *When bandwidth is maximal, the vote share is a step function:⁵*

$$\lim_{K_M \rightarrow \infty} p_A(g_M, K_M, \sigma) = \begin{cases} 1 & \text{if } \sigma < \frac{1}{2(1-g_M)} \\ 1/2 & \text{if } \sigma = \frac{1}{2(1-g_M)} \\ 0 & \text{if } \sigma > \frac{1}{2(1-g_M)} \end{cases}$$

⁵We assume that the the number of reportable news items N is infinitely larger than the number of items the voters observe/recall, K_M . This guarantees that a biased news source can choose any reporting policy. When we consider maximal bandwidth, we should therefore think of it as the limit as both K_M and N go to infinity with, for instance $K_M = \sqrt{N}$.

Now that we have characterized the vote share in each segment, let us move on to the overall vote share, and hence to characterizing the power of media group G .

Given any vector of segment bandwidth $K = (K_M)_{M \subset \mathbb{M}}$, the power of group G corresponds to the highest value of $\bar{\sigma}(K)$ such that the A -vote share is at least $1/2$, namely the solution to

$$\sum_{M \subset \mathbb{M}} q_{MP_A}(g_M, K_M, \bar{\sigma}(K)) = \frac{1}{2}.$$

If $\sum_{M \subset \mathbb{M}} q_{MP_A}(g_M, K_M, \bar{\sigma}(K)) \geq 1/2$ for all $\sigma \in [0, 1]$, we set $\bar{\sigma}(K) = 1$.

Define the power index of group G , for a given bandwidth vector K , as

$$\Pi(K) = 2\bar{\sigma}(K) - 1$$

The linear transformation from $\bar{\sigma}(K)$ to $\Pi(K)$ yields two properties. First, $\Pi(K) \in [0, 1]$ with 0 denoting no power (G has no influence on elections) and 1 denoting absolute power (G controls all elections). Second, as the valence of B is σ and the valence of A is $1 - \sigma$, the difference is $2\sigma - 1$. Hence, the value of $\Pi(K)$ corresponds to the maximal difference between the quality of candidate B (the better candidate) and the quality of candidate A (the candidate that wins thanks to G 's biased reporting).

Given this definition and Proposition 3, we immediately obtain a simple characterization of the power index:

Proposition 5 *For a given bandwidth vector K , the power of group G is $\Pi(K) = 2\bar{\sigma}(K) - 1$, where $\bar{\sigma}(K)$ is the minimum between one and the smallest solution greater than $1/2$ of the following polynomial equation:*

$$\sum_{M \subset \mathbb{M}} q_M \sum_{k=0}^{\lceil K_M/2 \rceil - 1} \binom{K_M}{k} ((1 - g_M) \bar{\sigma}(K))^k (1 - (1 - g_M) \bar{\sigma}(K))^{K_M - k} = \frac{1}{2}$$

As one would expect, the index is monotonic in g_M . An increase in the attention share of media group G in any segment causes an increase in $\bar{\sigma}(K)$ and hence in $\Pi(K)$. The increase is strict if $\Pi(K) < 1$.

Instead, the effect of K_M is non-monotonic. To see this, reconsider the two extreme cases of minimal and maximal bandwidth.

For the minimal case, suppose $K_M = 1$ in all segments. A 's overall vote share boils down to

$$1 - (1 - a_G) \sigma$$

where a_G is the attention share of media group G defined above. The power index is simply

$$\Pi(1) = \min\left(1, \frac{a_G}{1 - a_G}\right)$$

For the maximal case, instead we have.

$$\Pi(\infty) \equiv \lim_{K_M \rightarrow \infty, \text{ all } M} \Pi(K) = \min\left(1, \frac{\text{median}(g_M)}{1 - \text{median}(g_M)}\right),$$

where $\text{median}(g_M)$ is defined as G 's attention share for the median voter.⁶

If all voters follow at most two outlets, g_M can only take three values: 0, 1/2, and 1. This means that the power index takes only two values. If the reach of G is at least 50%, then power is absolute ($\Pi(\infty) = 1$). If it is 50% or less, the group has no power ($\Pi(\infty) = 1/2$).

To summarize the extreme cases:

Corollary 6 (i) *If bandwidth is minimal, media power is determined by attention share according to*

$$\Pi(1) = \min\left(1, \frac{a_G}{1 - a_G}\right)$$

(ii) *If bandwidth is maximal and no voter follows more than two outlets, media power is determined by reach according to*

$$\Pi(\infty) = \min\left(1, \frac{\text{median}(g_M)}{1 - \text{median}(g_M)}\right)$$

To illustrate the use of the power index in the extreme cases, return to the example and compute the power of individual media outlets.

Segment	Tv1	Tv2	Np1	Np2	Np3	Web1	Web2
$\Pi(1)$	0.333	0.164	0.176	0.090	0.101	0.176	0.152
$\Pi(\infty)$	0	0	0	0	0	0	0

With (uniform) maximal bandwidth, the power of all media outlets in this example is zero. This is because no individual outlet reaches 50% of consumers. If all voters have maximal bandwidth, the threshold for media influence is high. As we shall see

⁶Rank all voters in order of increase g_M and pick the one corresponding to mass 1/2. If this falls at the boundary between two segments, choose the segment with the lower g_M , a consequence of this being *the limit of a worst case*.

in the next section, maximal bandwidth in certain segments may instead make media more powerful if combined with minimal bandwidth in other segments.

One of the lessons of this analysis is that bandwidth is a key variable to determine media power. To compute the power index in Proposition 5, one must know the vector of segment bandwidth K . However, this knowledge may not be available in practice. It is also unlikely that bandwidth is the same across segments, as some voter groups have more time to devote to media or are more interested in news. This means that the worst-case scenario must be computed under the assumption that bandwidth is not known and may vary across segments, which is what we will discuss in the next section.

4 Power with Unknown Bandwidth

The previous section assumed that bandwidth was fixed and known. We now turn to the worst-case scenario under the assumption that the vector of bandwidth K is unobservable and potentially different for different segments. To compute the power of media group G , we must ask what vector K maximizes the value of σ such that Candidate A is still elected.

The key observation – which is shown formally in the proof of Proposition 7 – is that, for every value of g_M and σ , the maximal value of A 's vote share $p_A(g_M, K_M, \bar{\sigma})$ is achieved when either $K_M = 1$ or $K_M \rightarrow \infty$. This means that the upper envelope of A 's vote share over K_M is:

$$\max(p_A(g_M, 1, \sigma), p_A(g_M, \infty, \sigma))$$

This property becomes apparent in Figure 2. For every value of σ , the largest value of A 's vote corresponds to either $K_M = 1$ or $K_M \rightarrow \infty$. While this property simplifies the analysis, it is useful to keep in mind that it holds for a particular candidate quality σ and particular media attention share g_M .

Let $\bar{\sigma}$ the highest quality of candidate B for which M can still get candidate A elected. This is the same definition as in the previous section, except that now the maximal value is computed over all possible K -vectors. Similarly, the worst-case power index is defined as $\bar{\Pi} = 1 - \bar{\sigma}$. We are now ready to state the main result of the paper:

Proposition 7 *The power of group G is given by $\bar{\Pi} = 1 - \bar{\sigma}$ where $\bar{\sigma}$ is the minimum between one and the largest solution of*

$$\sum_{M \subset \mathcal{M}} q_M \max(p_A(g_M, 1, \sigma), p_A(g_M, \infty, \sigma)) = \frac{1}{2}$$

with

$$p_A(M, 1, \sigma) = 1 - (1 - g_M)\sigma$$

and

$$p_A(M, \infty, \sigma) \equiv \begin{cases} 0 & \text{if } (1 - g_M)\sigma \geq \frac{1}{2} \\ 1 & \text{if } (1 - g_M)\sigma < \frac{1}{2} \end{cases}$$

Proof. See Appendix. ■

To illustrate the use of Proposition 7, let us compute the maximal power of Website 1. Figure 3 below illustrates the procedure. We consider each segment separately.

In segments 1 through 5, Website 1 has no audience. The plot in the top left corner depicts A 's vote share for all values of $\sigma \in [0, 1]$ for three possible values of K_M : the diagonal line corresponds to $K = 1$ (namely $p_A(0, 1, \sigma)$); the step function corresponds to $K \rightarrow \infty$ ($p_A(0, \infty, \sigma)$); and the smooth curve in between corresponds to an intermediate value of K_M , in this case 5 ($p_A(0, 5, \sigma)$). The plot confirms what was shown in the proof of Proposition 7: the upper envelope of all $p_A(0, K_M, \sigma)$ functions – depicted in the top right corner – corresponds to either $K = 1$ or $K \rightarrow \infty$. The step occurs at $\sigma = 0.5$. This indicates that in a segment with no attention share, if $\sigma > 1/2$ the best case scenario for the evil owner is $K_M = 1$ as voters will be least informed and most likely to vote for A just because they make a mistake (the case with $\sigma < 1/2$ is uninteresting because A is elected even with unbiased reporting).

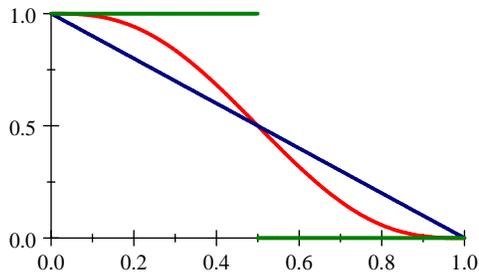
What happens in segments 6 and 10 is more interesting. Website 1 is one of four sources that voters follow: $g_M = 0.25$. The left plot on the second row from top depicts $p_A(0, K_M, \sigma)$ for $K_M = 1, 5$, and ∞ . The upper envelope is plotted to the right and it corresponds to $K_M \rightarrow \infty$ as long as $\sigma < 2/3$ and $K_M = 1$ thereafter. If $\sigma < 2/3$, the majority of news items that voters receive in those segments will be favorable to A . This is because they receive a share $1 - \sigma$ of A -favorable items from the three unbiased sources and 100% of A -favorable items from Website 1. The total share is therefore $0.75(1 - \sigma) + 0.25$, which is greater than $1/2$ if $\sigma \leq 2/3$. The best case scenario for the evil owner in segments 6 and 10 is $K_M \rightarrow \infty$ if $\sigma \leq 2/3$ and $K_M = 1$ if σ is larger.

The analysis of Segments 7 through 9 is analogous except that the threshold is greater, $\sigma = 3/4$, because Website 1 controls one third of the audience in those three segments.

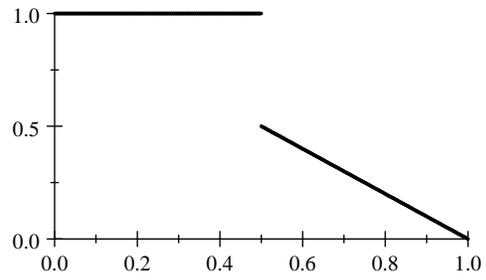
The bottom right plot depicts A 's vote share of the total population. It is a weighted average of the upper envelopes obtained for individual segments. The value of $\bar{\sigma}$ is the point where the vote share function is equal to $1/2$, which in this case

corresponds to a discontinuity point at $\bar{\sigma} = 0.75$. The corresponding power index is $\bar{\Pi} = 1/2$.

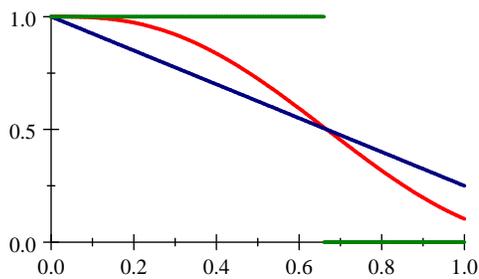
This means that maximal power is achieved when $K_{1-5} = 1$, $K_{6,10} = 1$, and $K_{7-9} \rightarrow \infty$. Under these conditions, for any $\sigma < 0.75$, Website 1 succeeds in getting A elected. When σ reaches 0.75, there is no vector of K_M that leads to the election of A .



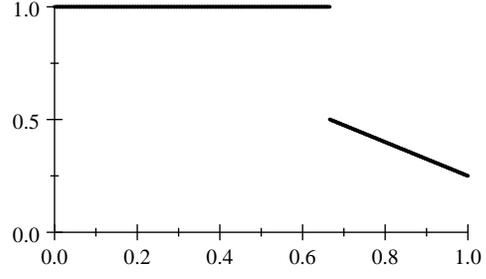
Segment 1-5



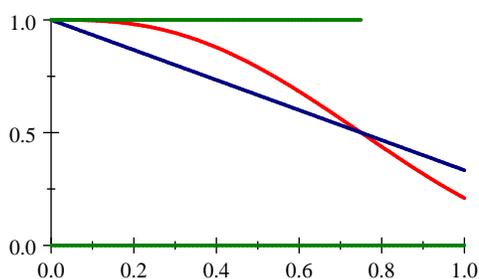
Segment 1-5: Worst Case



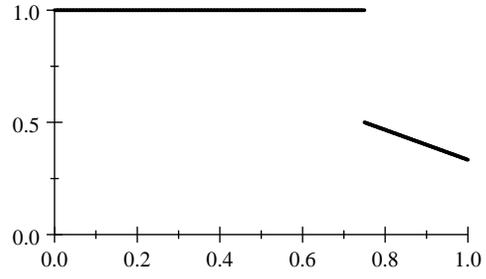
Segments 6 and 10



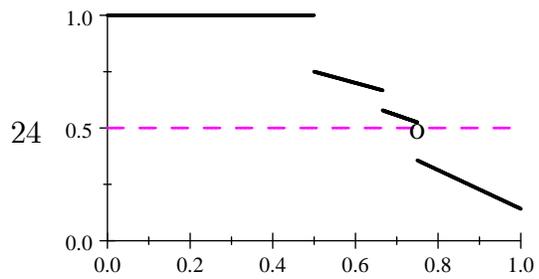
Segments 6 and 10: Worst Case



Segment 7-9



Segments 7-9: Worst Case



Overall Population

Figure 3 – Finding the Value of the Worst-Case Power index for Website 1

One can also compute the worst-case power index for each other news source, which is reported in the table below along with the minimal-bandwidth and maximal-bandwidth indices:

Segment	Tv1	Tv2	Np1	Np2	Np3	Web1	Web2
$\Pi(1)$	0.333	0.164	0.176	0.090	0.101	0.176	0.152
$\Pi(\infty)$	0	0	0	0	0	0	0
$\bar{\Pi}$	0.429	0.481	0.250	0.333	0.333	0.500	0.154

Given the discontinuous nature of the upper envelope function used to compute $\bar{\Pi}$, we were unable to find an analytical method for finding the value of the power index. However, as the function is monotonic and piecewise linear, a numerical method provides a fast and accurate approximation of the value of the index.⁷

4.1 Ideological Voters

The analysis can be readily extended to a situation where voters have ex ante opinion differences. The ideology of a voter is modeled as an array of signals that the voter received in the past. Ideological signals are binary and perform exactly the mathematical function of signals generated by unbiased media. By endowing a particular voter with the right number of *A*-leaning ideological signals and *B*-leaning ideological signals, we can achieve a continuum of ex ante opinions. For any assumption we make on voter ideology, we can provide a suitable re-statement of Proposition 7.

To illustrate this point, let us suppose that voters are divided in three groups: *A*-extremists, *B*-extremists, and moderates. *A*-extremists already have so many ideological signals in favor of *A* that, given their bandwidth, they would vote for *A* no matter what signals they receive from *B*. *B*-extremists are defined analogously. The remaining group of voters have no ideological signals. Proposition 7 can then be re-stated by restricting interest to agnostic voters, so that g_M represents no. The next section will also report power indices computed under the assumption that US voters can be divided into Democrats, Republicans, and independent voters.

5 Power Index of News Sources in the United States

This section applies the results proven above to the US media industry. We compute power indices for most major news sources in two ways, both suggested by the theory.

⁷The Stata approximation algorithm is available from the author upon request.

We first compute robust upper bounds, under an array of possible specifications. We then calibrate the model on the basis of an existing estimate of media influence and we compute power indices in that scenario.

5.1 Upper Bounds

To implement the methodology introduced in the previous section, we need a media consumption matrix, namely information about what news sources individual voters follow. This information is provided by the Media Consumption Survey, which has been conducted every other year since 1994 by the Pew Research Center. In 2012, this telephone-based survey covered approximately 3003 US residents and included 103 questions.

Questions refer to news consumption only, not entertainment. When covering a generalistic media outlet like CBS, NBC, or ABC, the interviewer asks explicitly about news programs, mentioning them by name, for example ABC World News with Diane Sawyer. The respondent is asked to specify whether he or she follows that particular source “regularly, sometimes, hardly ever or never”

Although we have data from 2000 to 2012, only the 2010 and 2012 editions of the survey cover all major news platforms: daily and weekly press, radio, television, and websites. Previous years are less complete and they become quite sparse in earlier editions. In 2000, the survey covered only a limited set of sources: news-only tv channels, radio stations, and magazines. In 2002, the survey was extended to the three major networks. In 2004, daily newspapers were added (as an aggregate source). In 2006, the Daily Show (Comedy Central) and the Rush Limbaugh Show were added. In 2008, the survey added websites. The respondent can indicate the three news sites he or she visits most often. “Google” indicates “Google News,” etc. In 2010, the survey began to include questions about for specific dailies: the New York Times, the Washington Post, USA Today, and the Wall Street Journal. We also have information on whether a particular news source is accessed through its traditional platform or through its website (e.g. New York Times and www.nytimes.com or Fox TV and www.foxnews.com). We combine this information under the same source.

Additional information about the data and the methodology is available in the *Notes of Data Sources and Index Computation* in the Appendix.

A “media conglomerate” is defined as a corporate entity that owns, directly or indirectly, a controlling stake in the companies that own the individual media sources on the basis of the situation in 2012. We identify three conglomerates: News Corp (Fox News and Wall Street Journal), Comcast (NBC and MSNBC), Time Warner (CNN, Comedy Central, Time Magazine).

One subtle question is to what extent certain new media sources should be considered original sources or neutral aggregators of content provided by other sources (George and Hogendorn 2013). Google News is the largest example of a pure aggregator while Yahoo News produces original content.⁸ For the purpose of the present exercise, we consider them as independent news sources. This can potentially overestimate the power of new media and underestimate the power of original news sources. However, as we shall see, index values for news aggregators are relatively low. So, assigning their influence to the original sources is unlikely to modify our main conclusions.

A key decision is to decide what constitutes media consumption. Some sources are used more frequently than others. One could think of ways of weighing attention by usage frequency (see suggestions for further research in the Conclusions). Here, we propose two definitions: a strict one including only sources that are used daily or almost daily and a loose definition that includes sources that are used at least weekly:

- **Daily Sources (Tables 2 and 4 and Figures 4, 5, 6, and 7).** Attention is restricted to news sources our respondents use on a daily, or almost daily, basis. This imposes two requirements: the source must be updated on a continuous or daily basis, like a website, a daily news program on radio or television, or a daily newspaper, and the respondent must report that he or she follows the source “regularly”. Table 2 provides information on media reach based on this stricter definition.

For each source, we compute both the worst-case index $\bar{\Pi}$ and the minimal-bandwidth index $\Pi(1)$ (the maximal-bandwidth index is almost always zero).

As surveys prior to 2010 cover fewer news sources, figures focus on the 2012 survey. Figure 4 and 5 represents worst-case power indices $\bar{\Pi}$ for individual news sources and conglomerates, respectively. Figure 6 reports minimal-bandwidth power indices $\Pi(1)$. The absolute levels are different – with $\bar{\Pi}$ ’s being roughly twice as large as the corresponding $\Pi(1)$ ’s. However, unlike in the example developed above, the relative rankings are almost identical for the two versions of the index, as highlighted in the scatterplot in Figure 7

The right-most column of Figures 4, 5, and 6 depict the power index of all daily newspapers except the four that are associated to specific questions: the

⁸Still, in our model a news aggregator could influence voter information by modifying the underlying algorithm to favor certain types of news. If this ability is unfettered, the aggregator has the same ability to affect reporting as any other news source.

New York Times, USA Today, the Wall Street Journal, and the Washington Post. The power index of all those dailies corresponds to a (counterfactual) assumption that all of them are under joint ownership. If they were, their power would be roughly equivalent to that of News Corp.

- **Weekly Sources (Table 3 and 5 and Figures 8 and 9).** We now focus on sources that are used on a weekly basis. We therefore include all daily sources that are followed “regularly” or “sometimes” and all weekly sources that are followed “regularly”.

Table 3 reports summary statistics on media reach. Table 5 reports both the worst-case index $\bar{\Pi}$ and the minimal-bandwidth version $\Pi(1)$.

Moving from daily to weekly news sources has limited effect on relative rankings. In fact, it seems to increase the relative strength of the three conglomerates. As one would expect, the key change is a reduction in the power of daily newspapers.

As discussed above, early Pew surveys had a more limited scope. Only 2010 and 2012 can be compared directly, and this is done in Figure 10. For most sources, differences are minimal. Time Warner lost some power mainly because of a drop in Comedy Central viewership. The four individually surveyed newspapers all gained ground, mostly because of increased website followers. The other newspapers lost ground (but we do not have direct information on internet use).

The usage of all major television networks has been monitored since 2004. Figure 11 reports their worst-case power indices from 2004 to 2014. The absolute values are not reliable because other news sources were added over time. However, it is interesting to examine the relative power. The Big Three (ABC, CBS, and NBC) and CNN have lost ground, while Fox, MSNBC, and PBS have fared relatively better. Finally, newspapers as a whole seem to have lost ground. Figure 12 depicts the total power that would accrue to a hypothetical owner of all US daily press from 2004 to 2012. There is a strong reduction, which stops in 2010.

The last robustness check concerns ideology. We perform an exercise based on the discussion at the end of Section 5. At the end of the Pew survey voters are asked to identify as Democrats, Republicans, Independents. Table 6 reports the media reach statistics and power index values for daily sources for 2012 computed on independent voters only (as well as those for the overall population for comparison transcribed from Tables 2 and 4). Power indices are quite similar for independents and general voters. They tend to be slightly lower, which is a consequence of the fact that independent voters have a slight tendency to follow more news sources than partisan

voters. Changes in the power of individual sources tends to depend on whether they are more or less likely to be followed by independent voters. Mainstream television appears to be underrepresented among independent voters (for instance MSNBC’s reach is 15.9% in the general population and 12.3% among independents) as well as some niche sources (Huffington Post and Rush Limbaugh). The sources that are over-represented among independents tend to be public-service media (NPR, PBS, BBC) and financial sources (Wall Street Journal, Bloomberg, Reuters). As a result of this, Comcast and Time Warner lose a little power while, thanks to the Wall Street Journal, News Corporation gains some ground.

To summarize, the empirical implementation based on the Pew data indicates that the power ranking of US media organizations, as defined here, is robust to a number of different specifications: defining media consumption on a daily or weekly basis, using a worst-case index or a minimal bandwidth index, using the 2010 or 2012 survey, and including all voters or independent voters only.

5.2 Calibration

In the previous subsection, the Media Power Index was computed under the assumption that voters are completely naive. Another possible route, which we explore now, is to calibrate the present model with existing estimates of media influence, thus inferring the level of naivete of voters and using it to compute media indices for all media organization.

Recall that in the model β represents the sophistication level of an individual voter, namely the prior probability that he knows that a media owner is biased. This leads to a model that is difficult to study except for $\beta = 0$. To simplify the analysis, we consider a slightly different definition of naivete. We assume that a share b of voters are completely sophisticated (and therefore $\beta = 1$) and a share $1 - b$ is completely naive ($\beta = 0$). The vote share of candidate A in segment M is thus

$$p_A(g_M, 1, \sigma, b) = (1 - b) ((1 - g_M)(1 - \sigma) + g_M) + b\sigma.$$

Thus, the power index is

$$\hat{\Pi}(b) = \frac{(1 - b) a_G}{1 - (1 - b) a_G},$$

which is the same expression as in Corollary 6 except that the attention share of media group a_G is now scaled down by the share of naive voters $1 - b$.

To determine b , we need a direct measure of the power of at least one media group. Della Vigna and Kaplan (2007) estimated the influence of Fox News on the 2000 US presidential elections. As the previous subsection showed that Fox News is the most

powerful US media source in terms of upper bounds, this is a natural starting point for calibrating our model. Between 1996 and 2000, Fox News was introduced in cable broadcasting in localities that comprise 35% of the US population. A difference-in-difference approach, controlling for fixed effects and voting trends, indicates that in areas where Fox News was introduced the Republican vote share increased by 0.4-0.7 percentage points, depending on the specification.

We will take the midpoint, namely a 0.55 percentage points effect, as the starting point of this calibration exercise. A vote share increase of 0.55 corresponds to a media power of 0.011.⁹ While in 2000, the 0.55 effect applied to 35% of the population who live in localities where Fox News was available, we assume that it now applies to the whole of the US, as Fox News is almost universally available.

Finally, we must take into account that Fox’s audience share has increased: according to Table 2, it went from 16.7% in 2000 to 27.6% in 2012 (Table 2). We assume that the attention share increased proportionally to the audience.¹⁰ The media power (with $K = 1$) of Fox News in 2000 was therefore

$$\Pi_{2000} = \frac{(1 - b) \frac{0.167}{0.276} a_{\text{fox2012}}}{1 - (1 - b) \frac{0.167}{0.276} a_{\text{fox2012}}}.$$

Replacing $\Pi_{2000} = 0.011$ and $a_{\text{fox2012}} = 0.163$ (from the 2012 Pew Survey), we obtain $b = 0.89$. This means that the media influence observed by Fox News in 2012 can be rationalized within our model if 89% of voters were sophisticated and the remaining 11% were naive.

This exercise presents two evident limits. First, it transposes an estimate obtained in a certain context and period to another context and period. The paper obviously does not claim that the calibrated estimates are correct. The goal of the exercise is just to illustrate what media power would look like under this assumption. Second, there is no guarantee that the original estimate represents the *maximal* influence that

⁹Our media power index is defined over the difference of the vote shares. If there are only two parties – as in our model – a 0.55 percentage points increase for the Republicans must correspond to a 1.1 points increase in the vote share difference. In a system with more than two candidates, this equivalence no longer holds (The additional Republican vote share might have come at the expense of the Democrats or Ralph Nader). However, the equivalence is likely to be a good approximation given that that 96.25% of the votes went to one of the two major parties.

¹⁰In 2000, Pew provides a good estimate of Fox News’ reach, but not of its attention share, because a number of important media sources, such as newspapers, were not in the survey. That is why we have to infer the change in attention share from the change in reach. This corresponds to assuming that the new Fox viewers follows as many alternative media sources as the original viewers.

Fox News can have on the political process. In this sense, these calibrated values should be seen as lower bounds.

On the basis of $b = 0.89$, Table 7 reports the power index values for all major US media groups. Power indices are approximately one magnitude order lower than under $\Pi(1)$ in Table 4. The most powerful organization is still News Corporation.

To interpret the size of the power index, consider the distribution of vote share difference of the two major parties in US presidential elections: namely [democratic votes - republican votes]/[democratic votes + republican votes]. In the last 50 years the mean is almost zero (0.008) and the standard deviation is 0.121. Recall that a media group is able to swing an election if the unbiased vote share difference is smaller than the value of the power index. Under a normal distribution, this means that a media group with power Π can swing a presidential election with probability $2\Phi(\Pi|0, 0.121) - 1$, where Φ is the Gaussian CDF. For News Corp this probability is 13.4%. Table 7 reports the swing probability thus computed for all major US media.

The calibration exercise confirms that media power is in the hands of traditional broadcasting. The three organizations with a swing probability greater than 5% are all (mainly) television companies: News Corp (13.4%), Comcast (9.8%), Time Warner (7.8%) The most powerful newspaper is still the New York Times with a swing probability of 2.2%. The whole press – even if they could behave as a unitary body – could swing only an election out of seven.

6 Discussion

6.1 Merger Analysis

Within the model, one can study the effect of media mergers.

For instance, in the example used throughout the paper, suppose that Tv1 is for sale and the owners of Newspaper1 and Website1 have expressed an interest in acquiring it. Which of the two buyers poses a larger risk? Note that, on their own, both acquirers have the same power under minimal bandwidth and maximal bandwidth.

Newspaper1 and Website1 have the same attention share – 15% – so under $K = 1$ the effect of a merger must be the same (Corollary 6, Part i). However, if bandwidth is maximal, or unknown, Website 1 becomes more dangerous, as the table below illustrates. Intuitively, this is because, when joint with Tv1 it has a sizeable presence in eight segments. At $\bar{\sigma} = \frac{10}{11} = 0.909$, it will still fully control segments 1,2, and 3 (30% of votes), and it will get an additional 20% of the overall votes from segments

6 through 10. At the same level of $\bar{\sigma}$, a group composed of Tv1 and Newspaper1 cannot get a majority for candidate A.

Segment	merging entities			merged entities	
	Tv1	Np1	Web1	Tv1+Np1	Tv1+Web1
1	100%			100%	100%
2	100%			100%	100%
3	50%	50%		100%	50%
4		100%		100%	
5					
6			25%		25%
7			33%		33%
8			33%		33%
9			33%		33%
10			25%		25%
$\Pi(1)$	0.333	0.176	0.176	0.833	0.833
$\Pi(\infty)$	0	0	0	0.500	0.749
$\bar{\Pi}$	0.429	0.250	0.500	0.833	0.909

Of course, merger analysis can be used on real data too. The Pew Media Consumption Survey can be used to compute the maximal power of a proposed merger. For instance, based on 2012 daily sources data, a hypothetical merger of ABC and CBS would create an entity with a power index of 0.250. That value would still be lower than the power indices of the three conglomerates: News Corp’s 0.419, Comcast’s 0.333, and Time Warner’s 0.286. Analogously, one could compute power indices for hypothetical mergers on the basis of calibrated values.

6.2 Conclusion

This paper has developed a media power notion based on two principles: the most disaggregate unit of analysis is the mind of voters and the power index is computed on the basis of the worst case over a set of possible assumptions on the beliefs and attention patterns of voters. The resulting media power index can be calculated for the United States on the basis of existing media consumption data.

This first attempt at quantifying media power highlights two lessons. First, the fact that Hirschmann-Hirshleifer Indices are low for most US media markets does not imply that media power is low too. Both the theoretical analysis and the empirical application indicate a large upper bound to the damage that media organizations can

inflict on the electorate. This is additional proof that standard competition analysis must be complemented with political economy concepts. The present approach identifies factors that determine the power of mass media, in particular voter beliefs and attention patterns: certain assumptions lead to zero power; other assumptions lead to very large index values. While beliefs and attention are not easy to measure, this paper shows that the way we model them determines our attitudes to media regulation.

Second, even with the limitations of the existing analysis, one platform stands out in terms of media power. The four most powerful media organizations in the US are mainly television providers. The most powerful radio station (NPR) is in the fifth position, the most powerful pure internet source (Yahoo) is sixth, and the most powerful pure press source (the New York Times) is tenth. This finding is highly robust to different specifications. While in the future other platforms may become more important, today's media regulators should be extremely wary of mergers involving large television organizations.

Third, if one is mainly interested in relative rankings, comparisons can be made on the basis of the simplest specification of the media power index – based on minimal bandwidth.

Fourth, one can use existing media influence measures to calibrate the model and obtain point estimates for every other media organization. As more empirical estimates of media influence become available, future research can extend and enrich the present model and produce structural estimates of media power.

An interesting issue is left for further research. The current definition of media consumption is binary: either a voter follows a news source or she does not. One could imagine incorporating information on how much time individuals devote to different sources, and that information is potentially available in the data.

References

- [1] Simon P. Anderson and John McLaren, Media Mergers and Media Bias with Rational Consumers, *Journal of the European Economic Association*, 2010.
- [2] Simon P. Anderson & Stephen Coate. Market Provision of Broadcasting: A Welfare Analysis. *Review of Economic Studies* 72(4): 947-972. 2005.
- [3] Ben H. Bagdikian. *The New Media Monopoly* (7th Ed.). Beacon Press. 2004.
- [4] David Balan, Patrick DeGraba, and Abraham L. Wickelgren. Ideological Persuasion in the Media. Working paper, 2009.

- [5] David Baron. Persistent Media Bias. *Journal of Public Economics* 90: 1–36. 2006.
- [6] Dan Bernhardt, Stefan Krasa, and Mattias Polborn. Political Polarization and the Electoral Effects of Media Bias. *Journal of Public Economics*. 98(5-6): 1092-1104. June 2008.
- [7] Timothy Besley and Andrea Prat. Handcuffs for the Grabbing Hand? The Role of the Media in Political Accountability. *American Economic Review*, 96(3): 720-736, June 2006.
- [8] Isabelle Brocas, Juan D. Carrillo, and Simon Wilkie. A Theoretical Analysis of the Impact of Local Market Structure on the Range of Viewpoints Supplied, *Federal Communications Commission Review of Media Ownership Rules*, Media Study No 9, 2010.
- [9] Gabriel Carroll. Robustness and Linear Contracts. Working Paper, Stanford University, 2013.
- [10] Sylvain Chassang. Calibrated Incentive Contracts. *Econometrica*. Forthcoming.
- [11] Sylvain Chassang and Gerard Padro i Miquel. “Corruption, Intimidation and Whistle-blowing: a Theory of Inference from Unverifiable Reports.” Working paper, Princeton University, 2013.
- [12] Fang Chiang and Brian Knight. Media Bias and Influence: Evidence from Newspaper Endorsements, July 2011, *Review of Economic Studies*, 78(3), 795-820.
- [13] John Duggan and Cesar Martinelli. A Spatial Theory of Media Slant and Voter Choice, *Review of Economic Studies*, vol. 78 (2011) 640-666.
- [14] Ruben Durante and Brian Knight. Partisan Control, Media Bias, and Viewer Responses: Evidence from Berlusconi’s Italy. *Journal of the European Economic Association*. June 2012.
- [15] Ruben Enikolopov, Maria Petrova, and Ekaterina Zhuravskaya. Media and Political Persuasion: Evidence from Russia. *American Economic Review*, December 2011, 111(7): 3253-85.
- [16] Matthew Gentzkow and Jesse Shapiro, Media Bias and Reputation. *Journal of Political Economy* 114(2): 280-316. April, 2006.

- [17] Matthew Gentzkow and Jesse Shapiro, "What Drives Media Slant? Evidence from U.S. Daily Newspapers", *Econometrica* 78, 2010, 35-71.
- [18] Matthew Gentzkow, Jesse M. Shapiro, and Michael Sinkinson. The Effect of Newspaper Entry and Exit on Electoral Politics, *American Economic Review* 101 (7). December 2011.
- [19] Matthew Gentzkow and Emir Kamenica, Competition in Persuasion. Working paper. University of Chicago. September 2012.
- [20] Lisa M. George. The Internet and the Market for Daily Newspapers. *BE Journal of Economic Analysis & Policy* 8:(1) 1935-1982. July 2008.
- [21] Lisa M. George and Christian Hogendorn. Local News Online: Aggregators, Geo-Targeting and the Market for Local News. Working paper, 2013.
- [22] Lisa M. George and Joel Waldfogel. Who Affects Whom in Daily Newspaper Markets? *Journal of Political Economy* 111(4): 765-784, 2003.
- [23] Emir Kamenica and Matthew Gentzkow. Bayesian Persuasion. *American Economic Review*. 101 (6). October 2011.
- [24] Eliana La Ferrara, Alberto Chong, and Suzanne Duryea. Soap Operas and Fertility: Evidence from Brazil. *American Economic Journal: Applied Economics* 4(4): 1-31. 2012.
- [25] Kristof Madarasz and Andrea Prat. Screening with an Approximate Type Space. CEPR Discussion Paper No. DP7900. 2010.
- [26] John McMillan and Pablo Zoido. How to Subvert Democracy: Montesinos in Peru. *Journal of Economic Perspectives* 18(4): 69-92. Fall 2004
- [27] Sendhil Mullainathan and Andrei Shleifer. The Market for News. *American Economic Review* 95: 1031–1053. 2005.
- [28] Eli M. Noam. *Media Ownership and Concentration in America*. Oxford University Press. 2009
- [29] Ofcom (2009). Second Public Service Broadcasting Review: Putting Viewers First. Available on www.ofcom.org.uk, January 2009.
- [30] OECD. Regulation and Competition Issues in Broadcasting in the Light of Convergence. DAFFE/CLP(99)1, 1999.

- [31] Maria Petrova. Mass Media and Special Interest Groups”, *Journal of Economic Behavior and Organization*, September 2012, 84(1), pp. 17-38
- [32] Michele Polo. Regulation for Pluralism in the Media Markets, in P.Seabright J. von Hagen (eds.) *Regulation of Media Markets*, Cambridge University Press. 2005;
- [33] Andrea Prat and David Stromberg. “The Political Economy of Mass Media,” *Advances in Economics and Econometrics: Theory and Applications*, Proceedings of the Tenth World Congress of the Econometric Society, 2012.
- [34] Riccardo Puglisi. Being the New York Times: the Political Behavior of a Newspaper. STICERD; London School of Economics, Political Economy and Public Policy (PEPP) Working Paper n. 20. 2006.

7 Appendix: Proofs

7.1 Proof of Lemma 2

First, it is easy to see, that, for any value of $\hat{s} \in [0, 1]$, $E[\sigma|Y, \hat{s}]$ is nonincreasing in the number of signals that are favorable to A . Hence, assume that all signals from biased media are zero's: $N_1(G) = 0$ and $N_0(G) = K_G$. Now the posterior is

$$E[\sigma|Y, \hat{s}] = \frac{\int_0^1 \sigma^{N_1(M/G)} (1 - \sigma)^{N_0(M/G)} \left((1 - \beta)(1 - \sigma)^{K_G} + \beta(1 - \hat{s}\sigma)^{K_G} \right) \sigma f(\sigma) d\sigma}{\int_0^1 \sigma^{N_1(M/G)} (1 - \sigma)^{N_0(M/G)} \left((1 - \beta)(1 - \sigma)^{K_G} + \beta(1 - \hat{s}\sigma)^{K_G} \right) df(\sigma) \sigma}$$

Second, let us show that $E[\sigma|Y, 1] \leq E[\sigma|Y, \hat{s}]$ for all $\hat{s} \in [0, 1]$. Note that $E[\sigma|Y, 1] \leq E[\sigma|Y, \hat{s}]$ if and only if

$$\begin{aligned} & \frac{\int_0^1 \sigma^{N_1(M/G)} (1 - \sigma)^{N_0(M/G)} (1 - \sigma)^{K_G} \sigma f(\sigma) d\sigma}{\int_0^1 \sigma^{N_1(M/G)} (1 - \sigma)^{N_0(M/G)} (1 - \sigma)^{K_G} df(\sigma) \sigma} \\ & \leq \frac{\int_0^1 \sigma^{N_1(M/G)} (1 - \sigma)^{N_0(M/G)} (1 - \hat{s}\sigma)^{K_G} \sigma f(\sigma) d\sigma}{\int_0^1 \sigma^{N_1(M/G)} (1 - \sigma)^{N_0(M/G)} (1 - \hat{s}\sigma)^{K_G} f(\sigma) d\sigma} \equiv \frac{A}{B}. \end{aligned}$$

Note that

$$\begin{aligned} & \text{sign} \left(\frac{d}{d\hat{s}} \frac{A}{B} \right) \\ = & \text{sign} \left(A \int_0^1 \sigma^{N_1(M/G)} (1-\sigma)^{N_0(M/G)} (1-\hat{s}\sigma)^{K_G-1} f(\sigma) d\sigma \right. \\ & \left. - B \int_0^1 \sigma^{N_1(M/G)} (1-\sigma)^{N_0(M/G)} (1-\hat{s}\sigma)^{K_G-1} \sigma f(\sigma) d\sigma \right) \end{aligned}$$

Note that

$$\frac{\int_0^1 \sigma^{N_1(M/G)} (1-\sigma)^{N_0(M/G)} (1-\hat{s}\sigma)^{K_G-1} f(\sigma) \sigma d\sigma}{\int_0^1 \sigma^{N_1(M/G)} (1-\sigma)^{N_0(M/G)} (1-\hat{s}\sigma)^{K_G-1} f(\sigma) d\sigma}$$

corresponds to $E[\sigma|\tilde{Y}, \hat{s}]$ where \tilde{Y} is Y less a biased signal that was favorable to A and therefore $E[\sigma|\tilde{Y}, \hat{s}] \geq E[\sigma|Y, \hat{s}] = A/B$. This proves that $\frac{d}{d\hat{s}} \frac{A}{B} \leq 0$. Thus, $\frac{A}{B}$ is minimized when $\hat{s} = 1$. This shows that the minimal value of $E[\sigma|Y, \hat{s}]$ is achieved when $\hat{s} = 1$. Thus, a lower bound to $E[\sigma|Y, \hat{s}]$ is

$$\frac{\int_0^1 \sigma^{N_1(M/G)} (1-\sigma)^{N_0(M/G)+K_G} \sigma d\sigma}{\int_0^1 \sigma^{N_1(M/G)} (1-\sigma)^{N_0(M/G)+K_G} d\sigma},$$

which corresponds to a situation where all the signal realizations coming from the biased media are zero and the public believes that biased media report truthfully.

$$\frac{\int_0^1 \sigma^{N_1(M/G)} (1-\sigma)^{N_0(M/G)+K_G} \sigma f(\sigma) d\sigma}{\int_0^1 \sigma^{N_1(M/G)} (1-\sigma)^{N_0(M/G)+K_G} f(\sigma) d\sigma} \quad (1)$$

7.2 Proof of Proposition 7

We wish to show that, for any given g_M , K_M , and σ , the value of $p_A(g_M, K_M, \sigma)$ is maximized either when $K_M = 1$ or when $K_M \rightarrow \infty$.

We prove this in two steps. First, note that, note that the summation over k in Proposition 3 goes from 0 to $\lceil K_M/2 \rceil - 1$. If K_M is an odd number, $\lceil K_M/2 \rceil = \lceil (K_M + 1)/2 \rceil$. For an odd K_M , this implies that $p_A(g_M, K_M, \sigma) \geq p_A(g_M, K_M + 1, \sigma)$. Therefore, if we wish to maximize p_A , we can focus on odd values of K_M .

Second, suppose we start with an odd positive integer K_M and we increase it by two to $K_M + 2$. As K_M is odd, we can write $\lceil K_M/2 \rceil - 1 = (K_M - 1)/2$: from

Proposition 3, the probability that a voter with K_M votes for B is equal to the probability that the majority of signals he receives are in favor of B :

$$p_A(g_M, K_M, \sigma) = \sum_{k=0}^{(K_M-1)/2} \binom{K_M}{k} ((1-g_M)\sigma)^k (1-(1-g_M)\sigma)^{K_M-k}$$

if we add two more signals, the probability that the majority of signals are in favor of B becomes

$$p_A(g_M, K_M + 2, \sigma) = \sum_{k=0}^{(K_M+1)/2} \binom{K_M + 2}{k} ((1-g_M)\sigma)^k (1-(1-g_M)\sigma)^{K_M+2-k}$$

Let x be the number of signals favorable to B that the voter observed with K_M . If either $x \leq (K_M - 3)/2$ or $x \geq (K_M + 3)/2$, then the two new signals cannot change the voter's decision.

If $x = (K_M - 1)/2$, the voter changes his decision (votes for B instead of A) if he gets two signals in favor of B , which happens with probability $((1-g_M)\sigma)^2$. If $x = (K_M + 1)/2$, the voter changes his decision (votes for A instead of B) if he gets two signals in favor of A , which happens with probability $(1-(1-g_M)\sigma)^2$. With the two additional signals, the probability that A is elected decreases if and only if

$$\begin{aligned} & \Pr(x = (K_M - 1)/2 | K_M \text{ signals}) ((1-g_M)\sigma)^2 \\ & - \Pr(x = (K_M + 1)/2 | K_M \text{ signals}) (1-(1-g_M)\sigma)^2 \\ & > 0 \end{aligned}$$

The inequality above corresponds to

$$\begin{aligned} & \binom{K_M}{K_M/2 - 1} ((1-g_M)\sigma)^{K_M/2-1} (1-(1-g_M)\sigma)^{K_M/2+1} ((1-g_M)\sigma)^2 \\ & > \binom{K_M}{K_M/2 + 1} ((1-g_M)\sigma)^{K_M/2+1} (1-(1-g_M)\sigma)^{K_M/2-1} (1-(1-g_M)\sigma)^2 \end{aligned}$$

Noting that

$$\binom{K_M}{(K_M - 1)/2} = \binom{K_M}{(K_M + 1)/2},$$

and performing some simplifications, we re-write the inequality as

$$((1-g_M)\sigma)^{K_M/2+1} (1-(1-g_M)\sigma)^{K_M/2+1} (2(1-g_M)\sigma - 1) > 0.$$

The two additional signals increase the the probability that B is elected if and only

$$(1 - g_M)\sigma > 1/2.$$

As this condition does not depend on K_M , for every M , every g_M , and every σ , the maximal K_M must be either the lowest or the highest possible value.

Notes on Data Sources and Index Computation

- The data was collected by the Biennial Media Consumption Survey, Pew Research Center.
- The scope of the survey has been expanded over time. As a result of these changes, power indices are not directly comparable across years. These are some of the major changes:
 - In 2000, the survey covered only a limited set of sources: news-only tv channels, radio stations, and magazines.
 - In 2002, the survey was extended to the three major networks.
 - In 2004, daily newspapers were added (as an aggregate source).
 - In 2006, the Daily Show (Comedy Central) and the Rush Limbaugh Show were added.
 - In 2008, the survey began to include questions about for specific dailies: the New York Times, the Washington Post, USA Today, and the Wall Street Journal.
 - In 2010, websites were added. The respondent can indicate the three news sites he or she visits most often. “Google” indicates “Google News,” etc.
- Starting in 2010, a respondent can indicate that he or she follows a particular media source in its traditional form or through its website. We combine the information. For instance, after 2010 “New York Times” indicates both the newspaper and www.nytimes.com.. Similarly, “Fox” indicates the television network as well as www.foxnews.com.
- Ownership of a news source is defined as ownership over the entity that makes editorial decisions for that source. So, *The Rush Limbaugh Show* is considered as owned by Mr Rush Limbaugh, even though he does not own the individual radio stations that broadcast it.
- A conglomerate is defined as a corporate entity that owns, directly or indirectly, a controlling stake in the companies that own the individual media sources. We define conglomerates based on the situation in 2012:
 - News Corp (which ceased to exist in 2013) controlled the Fox Broadcasting Company directly and the Wall Street Journal through Dow Jones & Co.
 - Comcast purchased a 51% stake in NBC Universal in 2009. MSNBC is a subsidiary of NBC Universal. In previous years, the conglomerate should be regarded as NBC Universal.
 - Time Warner owns CNN through Turner Broadcasting Systems, Comedy Central through HBO, and Time Magazine through Time Inc (Time Inc was spun off in 2013). Between 2000 and 2009 Time Warner owned AOL.
- The questions on weekly magazines are of the form “Time, Newsweek, or similar”. Individual shares cannot be disentangled. We assign all readers in the category to Time. Therefore, the media power of Time Warner is overestimated.
- The worst-case index $\bar{\Pi} = 2\bar{\sigma} - 1$ is approximated numerically:
 1. For each media source set initial value of $\sigma = .75$
 2. For each viewer, compute $s_1 = (1 - \text{attention share of media } i \text{ for viewer } j)\sigma$, and $s_{inf} = \begin{cases} 1 & : s_1 > 1/2 \\ 0 & : s_1 \leq 1/2 \end{cases}$
 3. Compute $\overline{s_{min}} = \frac{1}{n} \sum \min(s_1, s_{inf})$
 4. While $\overline{s_{min}} > 1/2$, decrease σ ; while $\overline{s_{min}} \leq 1/2$, increase σ
 5. Iterate until $\overline{s_{min}}$ is close to 1/2
- The minimal bandwidth index $\Pi(1)$ is computed analytically according to its definition.

Table 2: Daily Media Reach

News Source	Share of Followers						
	2000	2002	2004	2006	2008	2010	2012
AP/Reuters							0.003
Bloomberg							0.006
ABC		0.177	0.163	0.142	0.131	0.150	0.143
AOL					0.012	0.045	0.031
BBC					0.060	0.008	0.011
CBS		0.174	0.154	0.133	0.097	0.093	0.087
CNN	0.218	0.257	0.218	0.239	0.254	0.233	0.209
Drudge Report					0.002	0.017	0.015
PBS	0.051	0.053	0.054	0.049	0.054	0.058	0.079
Facebook						0.003	0.009
Fox	0.167	0.213	0.253	0.255	0.261	0.291	0.276
Google					0.006	0.066	0.055
Huffington Post						0.007	0.021
MSN					0.029	0.120	0.094
MSNBC	0.101	0.139	0.109	0.112	0.175	0.162	0.159
NBC		0.209	0.177	0.166	0.156	0.177	0.185
NPR	0.163	0.159	0.165	0.179	0.126	0.125	0.141
New York Times					0.008	0.066	0.079
USA Today					0.002	0.045	0.047
Wall Street Journal					0.004	0.050	0.056
Washington Post					0.003	0.010	0.017
Yahoo					0.029	0.140	0.126
C-SPAN	0.046	0.050	0.048	0.045	0.045	0.025	0.029
Comedy Central				0.058	0.051	0.082	0.063
Rush Limbaugh				0.059		0.060	0.063
Dailies (w/o NYT, WSJ, USAToday 2010+)			0.576	0.566	0.503	0.377	0.363
All Dailies			0.576	0.566	0.503	0.472	0.461
Conglomerates							
Time Warner (CNN, Comedy Channel, Time)	0.218	0.257	0.218	0.269	0.283	0.279	0.248
News Corporation (Fox, Wall Street Journal)	0.167	0.213	0.253	0.255	0.265	0.319	0.311
Comcast (NBC, MSNBC)	0.101	0.295	0.244	0.243	0.273	0.261	0.268

See Notes above for information on the data. This table includes all news sources that are updated on a daily basis or weekly basis.

The share of followers of a certain media source equals the number of respondents who follow that source over the total number of respondents.

For all media but websites, the table reports the share of respondents who follow a particular media source “regularly”. For websites, information about frequency of use is unavailable and the share includes all followers.

Table 3: Daily and Weekly Media Reach

News Source	Share of Followers						
	2000	2002	2004	2006	2008	2010	2012
AP/Reuters							0.003
Bloomberg							0.006
ABC		0.480	0.464	0.361	0.365	0.386	0.414
AOL					0.012	0.045	0.031
BBC					0.233	0.008	0.011
CBS		0.465	0.443	0.363	0.280	0.298	0.291
CNN	0.584	0.570	0.554	0.599	0.610	0.528	0.523
Drudge Report					0.002	0.017	0.015
PBS	0.194	0.209	0.220	0.242	0.186	0.238	0.300
Facebook						0.003	0.009
Fox	0.433	0.485	0.545	0.560	0.555	0.575	0.563
Google					0.006	0.066	0.055
Huffington Post						0.007	0.021
MSN					0.029	0.120	0.094
MSNBC	0.388	0.446	0.427	0.392	0.513	0.473	0.472
NBC		0.499	0.486	0.417	0.389	0.376	0.433
NPR	0.346	0.314	0.357	0.366	0.262	0.260	0.317
New York Times					0.008	0.162	0.197
USA Today					0.002	0.285	0.274
Wall Street Journal					0.004	0.186	0.204
Washington Post					0.003	0.010	0.017
Yahoo					0.029	0.140	0.126
C-SPAN	0.233	0.246	0.246	0.221	0.201	0.194	0.195
Comedy Central				0.196	0.177	0.297	0.311
Rush Limbaugh				0.157		0.166	0.188
Time, Newsweek	0.137	0.149	0.138	0.169	0.140	0.090	0.078
Weekly Business							0.036
Dailies (w/o NYT, WSJ, USAToday 2010+)			0.798	0.805	0.738	0.355	0.331
All Dailies			0.798	0.805	0.738	0.708	0.694
Fortune, Forbes	0.052	0.044	0.047	0.045	0.060		
People, US Weekly	0.055	0.057	0.064	0.074	0.049		
The Weekly Standard		0.017	0.022	0.024	0.019		
Conglomerates							
Time Warner (CNN, Comedy Channel, Time)	0.626	0.607	0.593	0.679	0.677	0.635	0.628
News Corporation (Fox, Wall Street Journal)	0.433	0.485	0.545	0.560	0.556	0.638	0.635
Comcast (NBC, MSNBC)	0.388	0.670	0.642	0.585	0.639	0.606	0.618

See Notes above for information on the data. This table includes all news sources that are updated on a daily or weekly basis.

The share of followers of a certain media source equals the number of respondents who follow that source over the total number of respondents. For all daily updated sources, we report the share of respondents who follow a particular media source “regularly”. For weekly updated sources, we report the share who follow a media source “regularly”. For websites, the share includes all followers.

Table 4: Power Index of Daily Sources

News Source	Π							$\Pi(1)$						
	2000	2002	2004	2006	2008	2010	2012	2000	2002	2004	2006	2008	2010	2012
AP/Reuters							0.004							0.001
Bloomberg							0.008							0.002
ABC		0.274	0.206	0.190	0.186	0.186	0.170		0.144	0.079	0.069	0.075	0.063	0.066
AOL					0.015	0.057	0.039					0.005	0.020	0.013
BBC					0.082	0.010	0.013					0.022	0.003	0.004
CBS		0.263	0.200	0.179	0.133	0.118	0.111		0.135	0.071	0.068	0.043	0.035	0.036
CNN	0.598	0.405	0.264	0.296	0.333	0.250	0.240	0.414	0.216	0.106	0.119	0.135	0.096	0.086
Drudge Report					0.003	0.021	0.019					0.001	0.006	0.006
PBS	0.120	0.084	0.071	0.063	0.073	0.073	0.102	0.064	0.026	0.022	0.020	0.016	0.017	0.025
Facebook						0.004	0.011						0.001	0.004
Fox	0.489	0.333	0.333	0.333	0.345	0.377	0.370	0.321	0.197	0.166	0.158	0.198	0.203	0.195
Google					0.008	0.084	0.071					0.002	0.023	0.022
Huffington Post						0.009	0.025						0.003	0.006
MSN					0.038	0.143	0.122					0.014	0.043	0.033
MSNBC	0.257	0.218	0.150	0.153	0.249	0.199	0.200	0.137	0.084	0.042	0.041	0.079	0.061	0.065
NBC		0.333	0.233	0.216	0.206	0.200	0.200		0.185	0.086	0.087	0.068	0.074	0.077
NPR	0.472	0.264	0.226	0.248	0.172	0.154	0.170	0.318	0.150	0.102	0.107	0.066	0.049	0.059
New York Times					0.010	0.084	0.101					0.002	0.026	0.031
USA Today					0.003	0.057	0.060					0.001	0.015	0.020
Wall Street Journal					0.005	0.063	0.071					0.002	0.017	0.018
Washington Post					0.004	0.012	0.020					0.001	0.003	0.005
Yahoo					0.038	0.171	0.162					0.015	0.067	0.057
C-SPAN	0.108	0.079	0.062	0.058	0.060	0.030	0.036	0.044	0.024	0.017	0.014	0.013	0.005	0.008
Comedy Central				0.076	0.068	0.106	0.081				0.023	0.021	0.034	0.028
Rush Limbaugh				0.077		0.075	0.082				0.022		0.016	0.022
Dailies (w/o NYT, WSJ, USAToday 2010+)			0.942	0.771	0.624	0.426	0.407			0.594	0.502	0.412	0.233	0.214
All Dailies			0.942	0.771	0.624	0.500	0.500			0.594	0.502	0.412	0.279	0.262
Conglomerates														
Time Warner (CNN, Comedy Channel, Time)	0.598	0.405	0.264	0.333	0.333	0.333	0.286	0.414	0.216	0.106	0.148	0.163	0.136	0.120
News Corporation (Fox, Wall Street Journal)	0.489	0.333	0.333	0.333	0.351	0.414	0.419	0.321	0.197	0.166	0.158	0.200	0.228	0.221
Comcast (NBC, MSNBC)	0.257	0.500	0.333	0.319	0.333	0.333	0.333	0.137	0.305	0.135	0.135	0.160	0.144	0.153

See Notes above for information on the data. This table includes all news sources that are updated on a daily basis (at least five times a week). The share of followers of a certain media source equals the number of respondents who follow that source over the total number of respondents. For all media but websites, the table reports the share of respondents who follow a particular media source “regularly”. For websites, information about frequency of use is unavailable and the share includes all followers

Table 5: Power Index of Daily and Weekly Sources

News Source	Π							$\Pi(1)$						
	2000	2002	2004	2006	2008	2010	2012	2000	2002	2004	2006	2008	2010	2012
AP/Reuters							0.004							0.000
Bloomberg							0.006							0.001
ABC		0.320	0.250	0.200	0.200	0.200	0.200		0.136	0.098	0.069	0.075	0.070	0.073
AOL					0.013	0.049	0.033					0.002	0.009	0.004
BBC					0.149	0.008	0.012					0.040	0.001	0.002
CBS		0.295	0.250	0.200	0.171	0.167	0.162		0.129	0.093	0.070	0.053	0.049	0.045
CNN	0.518	0.333	0.271	0.333	0.333	0.231	0.222	0.359	0.177	0.125	0.164	0.152	0.097	0.095
Drudge Report					0.002	0.018	0.016					0.000	0.002	0.002
PBS	0.232	0.167	0.152	0.143	0.125	0.142	0.151	0.074	0.046	0.039	0.038	0.028	0.035	0.043
Facebook						0.003	0.009						0.000	0.002
Fox	0.495	0.333	0.299	0.333	0.372	0.435	0.400	0.235	0.157	0.142	0.166	0.187	0.229	0.202
Google					0.007	0.068	0.059					0.001	0.010	0.008
Huffington Post						0.008	0.022						0.001	0.003
MSN					0.031	0.094	0.083					0.005	0.016	0.014
MSNBC	0.366	0.266	0.228	0.191	0.286	0.275	0.250	0.182	0.118	0.087	0.067	0.122	0.114	0.104
NBC		0.333	0.250	0.205	0.200	0.200	0.200		0.144	0.104	0.083	0.076	0.068	0.075
NPR	0.366	0.250	0.219	0.200	0.167	0.143	0.167	0.187	0.102	0.086	0.079	0.049	0.044	0.058
New York Times					0.008	0.111	0.134					0.001	0.024	0.032
USA Today					0.002	0.149	0.145					0.000	0.045	0.042
Wall Street Journal					0.005	0.125	0.130					0.001	0.026	0.029
Washington Post					0.003	0.010	0.017					0.000	0.001	0.002
Yahoo					0.031	0.111	0.106					0.006	0.027	0.021
C-SPAN	0.250	0.184	0.167	0.139	0.128	0.125	0.111	0.083	0.051	0.042	0.031	0.028	0.025	0.024
Comedy Central				0.143	0.127	0.200	0.200				0.033	0.033	0.061	0.069
Rush Limbaugh				0.134		0.125	0.140				0.032		0.026	0.031
Time, Newsweek	0.171	0.143	0.125	0.131	0.118	0.083	0.073	0.052	0.034	0.024	0.028	0.023	0.012	0.010
Weekly Business							0.039							0.005
Dailies (w/o NYT, WSJ, USAToday 2010+)			0.469	0.402	0.351	0.247	0.224			0.266	0.242	0.213	0.103	0.092
All Dailies			0.469	0.402	0.351	0.313	0.285			0.266	0.242	0.213	0.168	0.159
Fortune, Forbes	0.066	0.050	0.051	0.049	0.067			0.016	0.011	0.009	0.006	0.010		
People, US Weekly	0.069	0.065	0.071	0.078	0.055			0.024	0.017	0.012	0.014	0.010		
The Weekly Standard		0.019	0.023	0.025	0.021				0.004	0.004	0.003	0.003		
Conglomerates														
Time Warner (CNN, Comedy Channel, Time)	0.706	0.415	0.333	0.500	0.429	0.391	0.375	0.457	0.224	0.156	0.250	0.228	0.188	0.191
News Corporation (Fox, Wall Street Journal)	0.495	0.333	0.299	0.333	0.375	0.497	0.470	0.235	0.157	0.142	0.166	0.188	0.268	0.244
Comcast (NBC, MSNBC)	0.366	0.500	0.400	0.333	0.429	0.401	0.400	0.182	0.300	0.210	0.161	0.219	0.200	0.196

See Notes above for information on the data. This table includes all news sources that are updated on a daily or weekly basis. The share of followers of a certain media source equals the number of respondents who follow that source over the total number of respondents. For all media but websites, the table reports the share of respondents who follow a particular media source “regularly”. For websites, information about frequency of use is unavailable and the share includes all followers.

Table 6: Independent Voters: Reach and Power (2012, Daily)

Company	Independents			All Voters		
	Share	$\bar{\Pi}$	$\Pi(1)$	Share	$\bar{\Pi}$	$\Pi(1)$
AP/Reuters	0.006	0.008	0.002	0.003	0.004	0.001
Bloomberg	0.013	0.016	0.004	0.006	0.008	0.002
ABC	0.112	0.143	0.053	0.143	0.170	0.066
AOL	0.044	0.057	0.018	0.031	0.039	0.013
BBC	0.013	0.016	0.006	0.011	0.013	0.004
CBS	0.082	0.109	0.036	0.087	0.111	0.036
CNN	0.188	0.223	0.082	0.209	0.240	0.086
Drudge Report	0.017	0.021	0.006	0.015	0.019	0.006
PBS	0.074	0.096	0.026	0.079	0.102	0.025
Facebook	0.013	0.016	0.006	0.009	0.011	0.004
Fox	0.256	0.353	0.180	0.276	0.370	0.195
Google	0.059	0.078	0.025	0.055	0.071	0.022
Huffington Post	0.015	0.018	0.005	0.021	0.025	0.006
MSN	0.089	0.118	0.034	0.094	0.122	0.033
MSNBC	0.123	0.160	0.049	0.159	0.200	0.065
NBC	0.171	0.200	0.076	0.185	0.200	0.077
NPR	0.150	0.200	0.073	0.141	0.170	0.059
New York Times	0.074	0.099	0.028	0.079	0.101	0.031
USA Today	0.038	0.049	0.017	0.047	0.060	0.020
Wall Street Journal	0.080	0.108	0.030	0.056	0.071	0.018
Washington Post	0.019	0.024	0.006	0.017	0.020	0.005
Yahoo	0.129	0.167	0.058	0.126	0.162	0.057
C-SPAN	0.027	0.035	0.007	0.029	0.036	0.008
Comedy Central	0.063	0.083	0.037	0.063	0.081	0.028
Rush Limbaugh	0.044	0.057	0.015	0.063	0.082	0.022
Dailies (w/o NYT, WSJ, USAToday 2010+)	0.351	0.431	0.219	0.363	0.407	0.214
All Dailies	0.448	0.500	0.266	0.461	0.500	0.262
Conglomerates						
Time Warner (CNN, Comedy Channel, Time)	0.241	0.279	0.125	0.248	0.286	0.120
News Corporation (Fox, Wall Street Journal)	0.304	0.434	0.222	0.311	0.419	0.221
Comcast (NBC, MSNBC)	0.235	0.324	0.132	0.268	0.333	0.153

See Notes above for information on the data. This table includes all news sources that are updated on a daily basis (at least fivetimes a week). The share of followers of a certain media source equals the number of respondents who follow that source over the total number of respondents. For all media but websites, the table reports the share of respondents who follow a particular media source “regularly”. For websites, information about frequency of use is unavailable and the share includes all followers.

Table 7: Calibration (2012, Daily)

Company	$\Pi(1)$	Swing Proba
AP/Reuters	0.0001	0.0007
Bloomberg	0.0002	0.0013
ABC	0.0068	0.0449
AOL	0.0014	0.0093
BBC	0.0004	0.0026
CBS	0.0038	0.0251
CNN	0.0088	0.0581
Drudge Report	0.0006	0.0040
PBS	0.0026	0.0172
Facebook	0.0005	0.0033
Fox	0.0183	0.1205
Google	0.0023	0.0152
Huffington Post	0.0007	0.0046
MSN	0.0035	0.0231
MSNBC	0.0068	0.0449
NBC	0.0079	0.0522
NPR	0.0062	0.0410
New York Times	0.0033	0.0218
USA Today	0.0021	0.0139
Wall Street Journal	0.0020	0.0132
Washington Post	0.0005	0.0033
Yahoo	0.0060	0.0396
C-SPAN	0.0008	0.0053
Comedy Central	0.0030	0.0198
Rush Limbaugh	0.0024	0.0159
Dailies (w/o NYT, WSJ, USAToday 2010+)	0.0198	0.1303
All Dailies	0.0234	0.1537
Conglomerates		
Time Warner (CNN, Comedy Channel, Time)	0.0119	0.0785
News Corporation (Fox, Wall Street Journal)	0.0203	0.1336
Comcast (NBC, MSNBC)	0.0148	0.0976

Media power indices are computed under the assumption that 11% of voters are naive and $K = 1$. The value is chosen to ensure the 2000 media power index of Fox News matches the midpoint of the vote share influence estimates in Della Vigna and Kaplan (2007). Swing Probability is based on the vote share distribution in US Presidential elections in the last 50 years.

Figure 4: Worst-Case Power Index: Individual Daily Sources, 2012

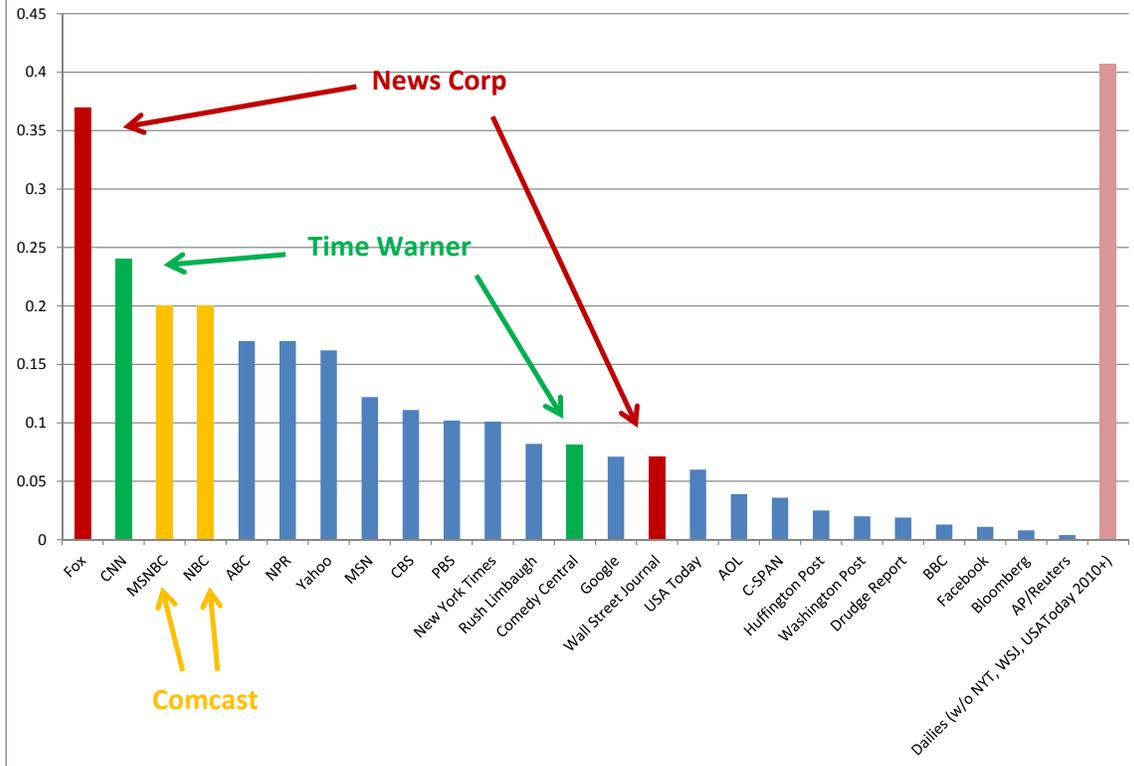


Figure 5: Worst-Case Power Index: Daily Sources with Conglomerates, 2012

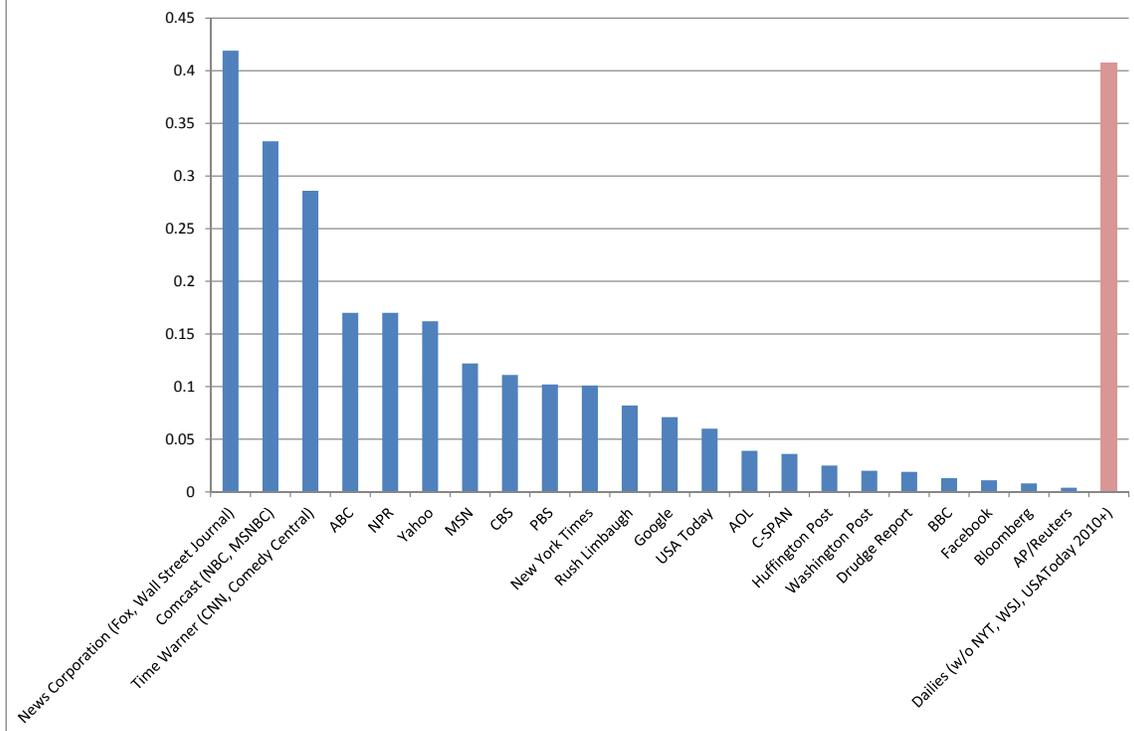


Figure 6: Minimal Bandwidth Power Index: Daily Sources, 2012

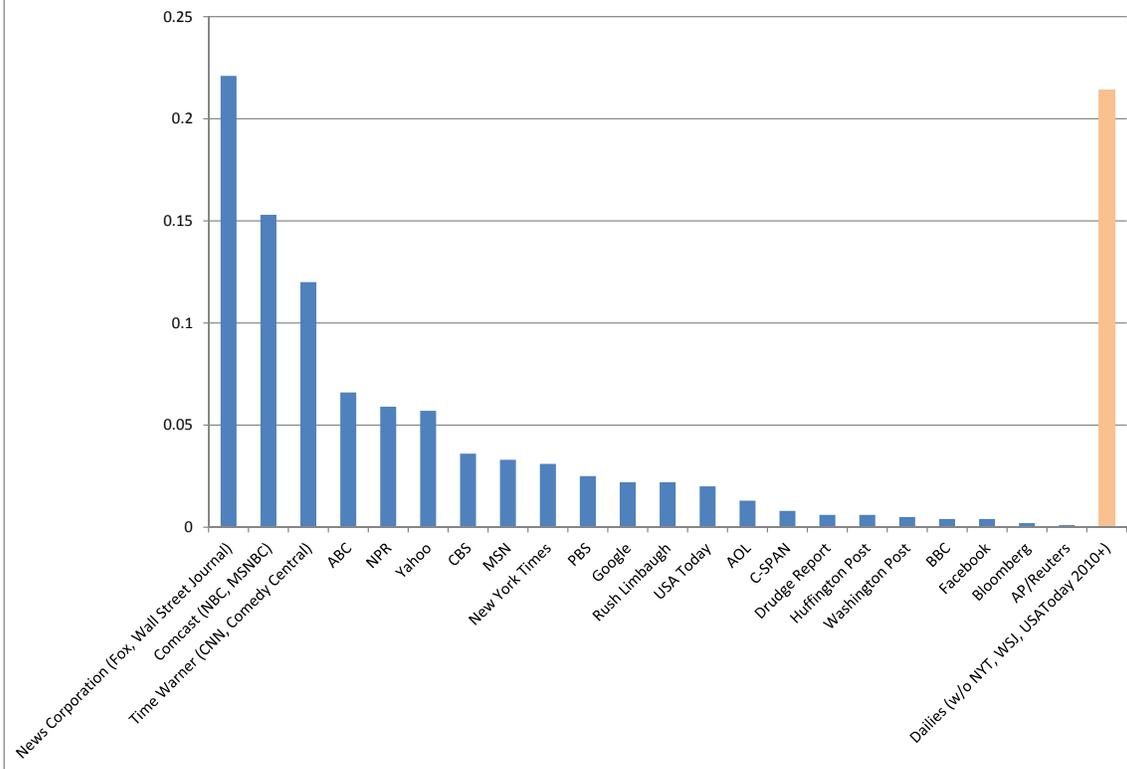


Figure 7: Worst-Case Power and Minimal-Bandwidth Power

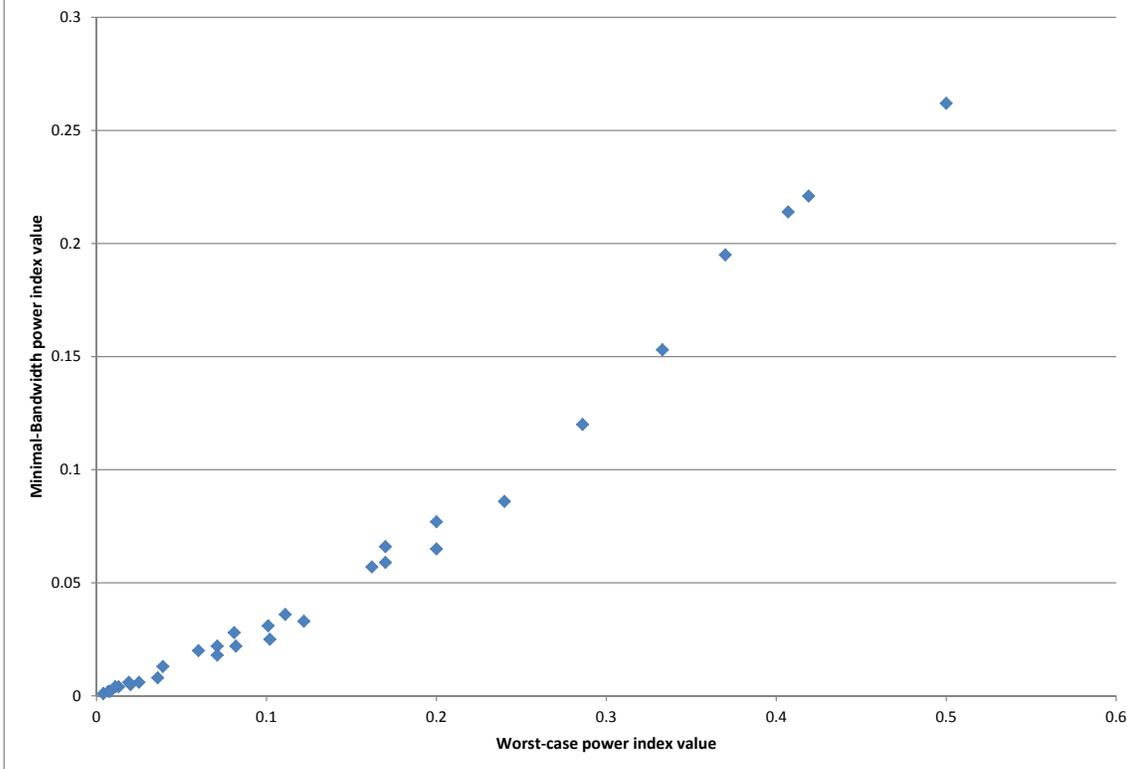


Figure 8: Worst-Case Power Index: Daily and Weekly Sources, 2012

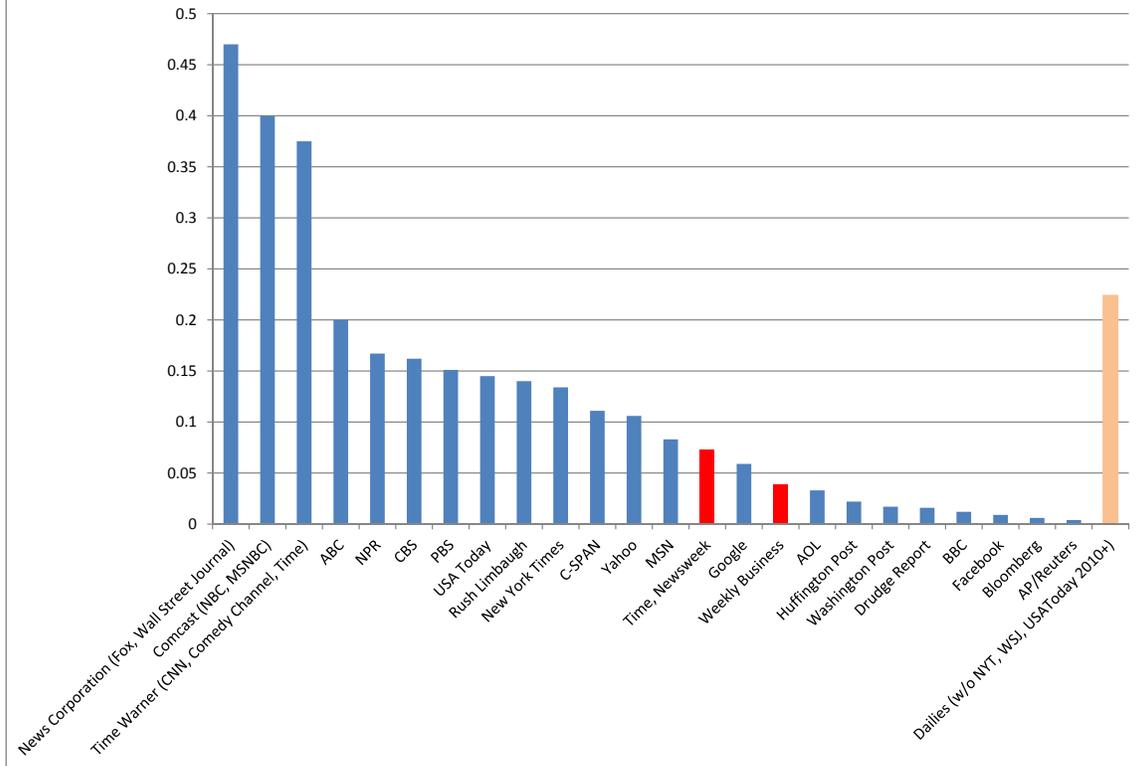


Figure 9: Minimal Bandwidth Power Index: Daily and Weekly Sources, 2012

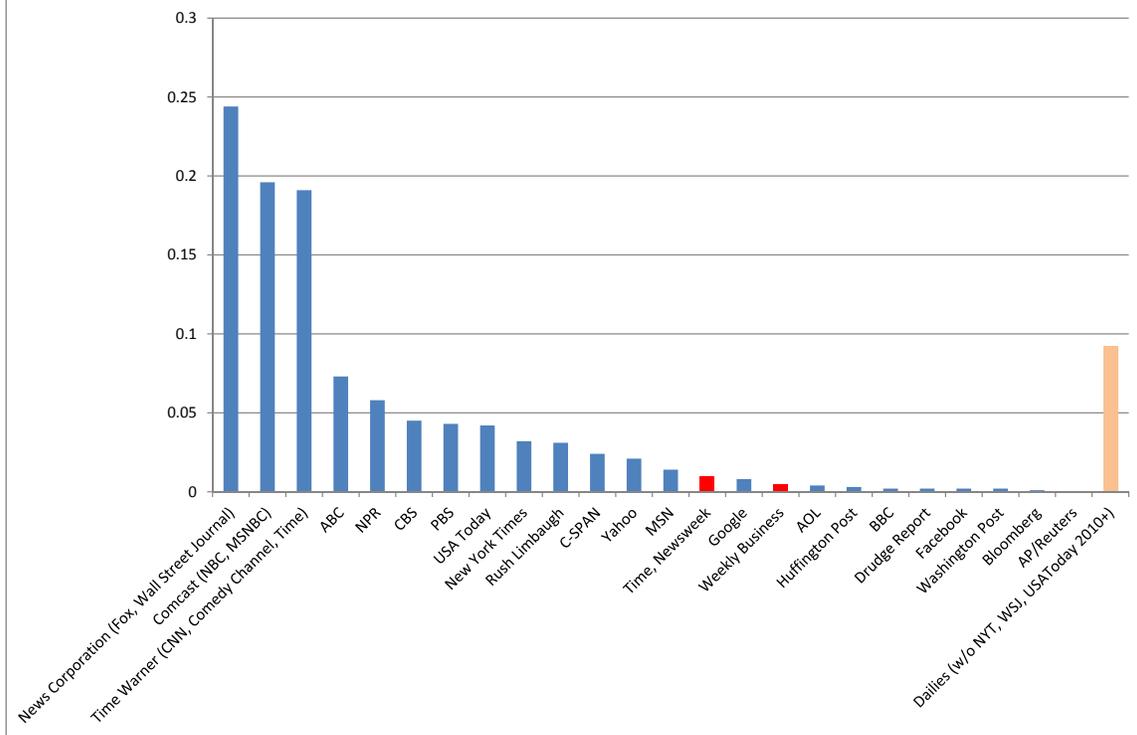


Figure 10: Evolution of Media Power from 2010 to 2012

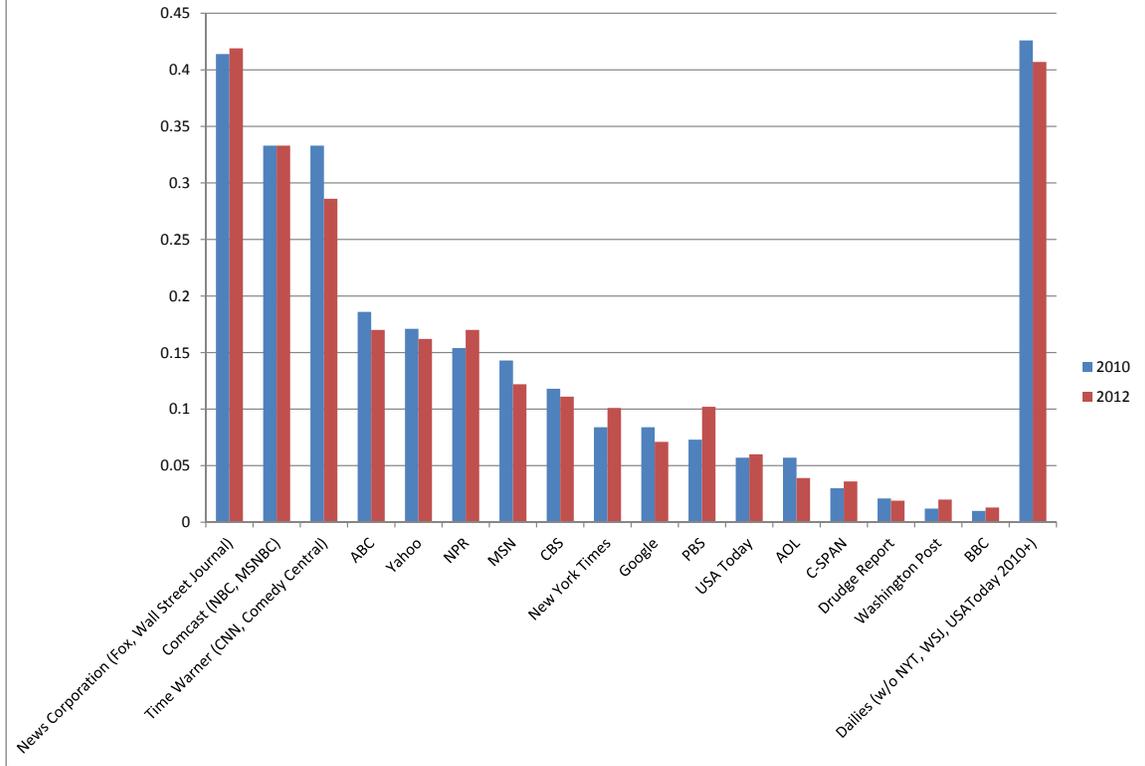


Figure 11: Evolution of TV Power (2002-2012)

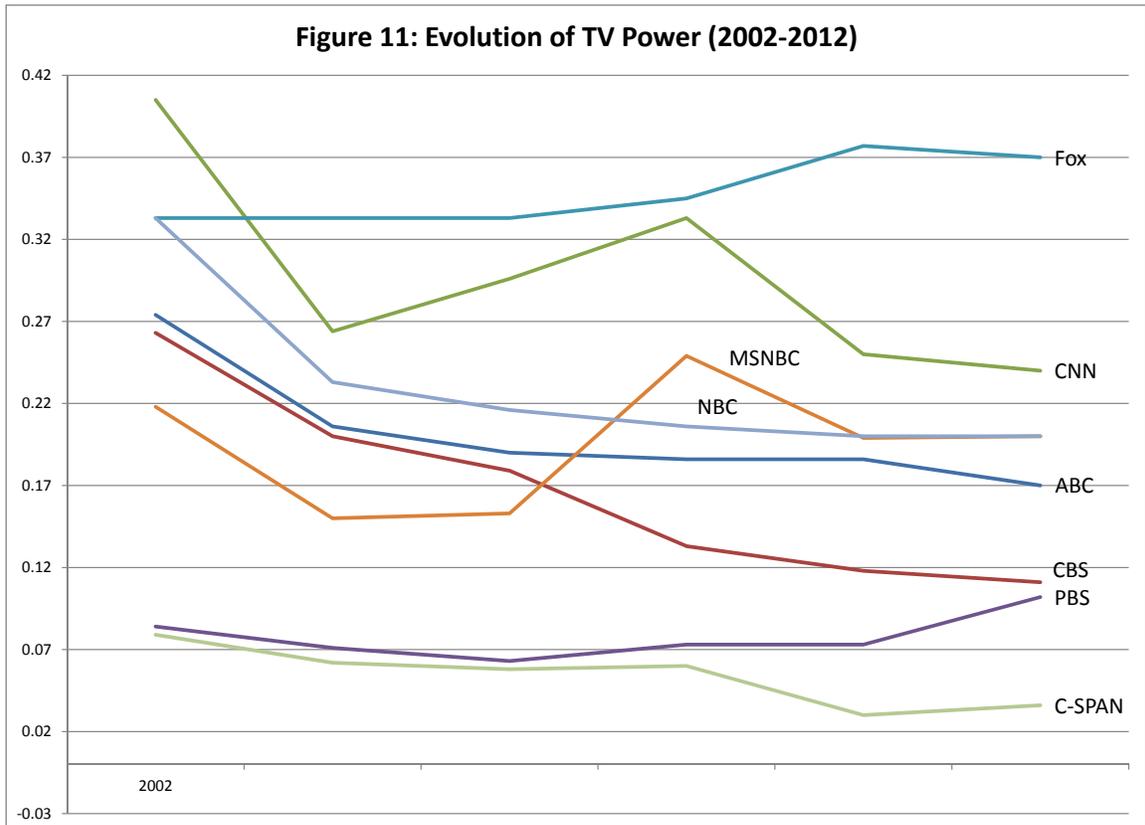


Figure 12: Evolution of the Power of Daily Newspapers (2004-2012)

