Media Power

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Abstract

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. It proposes a measure of power with two features. First, while existing concentration indices are built by aggregating market shares across platforms, the new measure performs cross-platform aggregation at the voter level. Second, rather than relying on a particular model of media influence, the paper derives a robust upper bound to media power over a range of assumptions on the beliefs and attention patterns of voters. Index values can be computed for the US in 2012 and reveal the following patterns. 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 calibration exercise shows how empirical estimates of media influence can be used to refine the power index.

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1 Introduction[1]

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

[1] As this paper is based on a somewhat non-standard approach for both theory and empirics, an extended introduction – organized into sections – is useful to explain the paper's methodology and how it relates to the debate on media concentration.

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).[2]

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.[3] 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 per-

[2]Political 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 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.

[3]For 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."

form 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, how can we answer this question before the attempt actually occurs?

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 an individual voter. 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 – how will voters react to an attemp to manipulate their views? – there are two possible approaches. Ideally, we would have a precise model of how the voters and the media behave and we would use 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. One could of course choose an arbitrary way of modeling the behavior of voters and media, but the resulting power measure would be equally arbitrary.

This paper instead acknowledges the difficulty of identifying a model of voter behavior and adopts a different approach, inspired by a recent literature on "robust bounds" in agency problems (Chassang 2013, Madarasz and Prat 2011, Carroll 2014, and Chassang and Padro i Miquel 2013). A standard agency-theoretic problem assumes that the principal has a – possibly probabilitic – 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. 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 goal of the theory section is to show how the approach discussed above can be implemented for a given set of models.

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.[4]

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.

The theoretical contribution of the paper lies in the analysis of the upper bound to media power for a set of models of voter and media behavior. 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.

[4] The analysis can be extended to multiple biased owners, whether their biases go in the same or in opposite directions. See discussion in page 15.

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. In line with the worst-case spirit of the analysis, it is assumed that voters do not switch away from media sources that become biased.

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 output of the analysis is a mapping from a media consumption matrix into a power index for each possible subset of media sources.

The set of models under consideration is large, but it can still be extended in many directions. In the paper we study one particularly important extension. While in the baseline case voters differ only in terms of media consumption, the model can be extended to include an ideological dimension, which can be captured as a set of signal realizations that each voter receives before the game starts. This endows each voter with an arbitrary prior distribution over candidate quality. The set of media sources that the voter follows is allowed to depend on his ideology. The conclusion discusses other possible extensions.

Empirics Previous indices, such as the Media Diversity Index, made assumptions on the relative influence of different platforms and the relative influence of sources within each platform. At a conceptual level, these assumptions were not derived from a micro-founded framework. At a practical level, it was difficult to decide what the weights should be and how they should evolve over time. The media power index overcomes this problem by assigning influence weights to media sources on the basis of individual media consumption patterns. However, this means that the media power index cannot be computed from market share information: it requires *individual-level news consumption data covering all media platforms.* Fortunately, for the United States this information is available from the Media Consumption Survey run every even year by the Pew Research Center.

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 existing estimates of media 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 Center. 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, and on the probability of abstention. The relative ranking of the major media organizations is highly stable across specifications.

Upper bounds can be computed not just at the US level, but also for smaller jurisdictions. We illustrate this possibility by computing the power indices of media organizations in New York State.

The calibration exercise consists in utilizing available estimates of media power to restrict the set of models under consideration. The paper illustrates this approach with estimates from Della Vigna and Kaplan (2007) for broadcast media and Gentzkow, Shapiro and Sinkinson (2011) and Chiang and Knight (2011) for the press. The former obtain a positive and significant estimate of the influence of Fox News on voting patterns, the latter obtain a zero effect for newspapers. Our calibration exercise assumes that Della Vigna and Kaplan (2007) represents an upper bound for all viewing-based media and the other two papers represent an upper bound for all reading-based media. We obtain power indices for the same set of media organizations considered above. The values of the index are one order of magnitude lower than in the theoretical upper-bounds case. The relative ranking is mostly unchanged, as the assumption that readers are sophisticated reduces the relative power of sources that were already ranked low.

Findings The theoretical and empirical analyses yield four (tentative) results.

First, some media organizations display very large power indices. In the minimal bandwidth case, News Corp could control elections with a vote share difference of 22

percentage points, which would have been enough to swing 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 worst-case scenario indices.

This result, which stands in contrast with the fact that standard concentration measures are not particularly high in any US media market (Noam 2009), highlights the importance of examining media concentration at the individual level rather than at the platform level. The magnitude orders of media power in this paper are a consequence of the fact that a small number of media organizations control large attention shares. Unless *almost all* those voters are highly responsive to attempts to manipulate them, attention concentration will translate into large potential influence. Even a small share of naive voters (in the calibration exercise 91% of voters are immune from manipulation) leads to sizeable power indices. Of course, being an upper bound result, this finding does not mean that media conglomerates *can or 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.

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), our findings imply that ownership of television networks should continue to be 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 use existing empirical estimates to refine the power index. This is not asssumption-free, as it corresponds to

putting a cap on media influence based on evidence about specific media in specific episodes. However, as the empirical literature on mass media continues to produce 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 increasingly confident upper bounds predictions on the effect of mergers and other structural changes in the media industry.

The next section contains a brief review of the literature. Section 3 describes the model and characterizes the benchmark case where all media outlets are unbiased. Section 4 introduces an evil owner and studies power when the voter bandwidth is known. Section 5 derives the worst-case power index. Section 6 contains the empirical analysis. Section 7 concludes by mentioning policy implications including merger analysis.

2 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, Shapiro and Sinkinson (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: demand or supply. On the demand side, consumers may prefer biased coverage, either directly because of cognitive biases (Mullainathan and Shleifer 2005) or indirectly because they rationally put more trust in sources that report information that con-

forms to their prior beliefs (Gentzkow and Shapiro 2006). Under demand-driven bias, media owners will supply biased information not because of their political preferences but because biased reporting is the optimal profit maximization strategy. This type of bias is well-documented (e.g. Gentzkow and Shapiro 2010). Under pure demand bias, replacing the owner of a media organization with another owner has no effect on reporting: as they are both profit maximizers, they will choose the same strategy. Bias can also be supply driven. Media owners manipulate news reporting not just to satisfy their customers' preferences, but also for their own goals (Baron 2006, Besley and Prat 2006, Balan, De-Graba, and Wickelgren 2009, Duggan and Martinelli 2011, Anderson and McLaren 2012, Petrova 2012). Besley and Prat (2006) assume that the goal of news manipulation is to influence the electoral process and they 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 media bias 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.

Regarding the distinction between demand-driven and supply-driven bias, the paper assumes that the media consumption matrix reflects current demand for news and measures the upper bound to the effect that media owners can achieve through supply-side bias. As it will become transparent in the analysis, finding the upper bound involves making a number of assumptions that maximize the potential role for supply-driven bias (see the five assumptions in page 4).

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 bandwdth: 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.[5]

3 Unbiased Media

The theory part of the paper is divided in three sections. This section introduces the model and analyzes a benchmark case with no media bias (Proposition 1). Section 4 contains the main result of the paper: a characterization of the power index in terms of media consumption patterns (Proposition 5). Proposition 2 requires knowledge of the cognitive skills of voters. So Section 5 contains the worst-case characterization when cognitive skills are unknown (Proposition 7).

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.[6] 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.

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 $x_m = (x_{m1}, ..., x_{mN})$ denote a vector of N binary signals – *news items* – observed by outlet m, with $\Pr(x_{mi} = 1) = \sigma$. News items are, conditional on σ, independent within and across media outlets.

[5] The 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.

[6] The 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.

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 $q_{\varnothing} = 0$. This makes no difference provided that voters who receive no messages vote randomly.

Table 1 contains a 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 follows: 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.[7]

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

[7]In reality, the media consumption matrix is not exogenous. It depends on the ideological positions of voters and it can be affected by the behavior of media sources. This point is discussed in the next section.

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 $\#M \times N$ signals.

However, voters have potentially limited *bandwidth*. Voters in segment M observe or remember a limited number $K_M \in \{1, ..., N\}$ of news items, randomly selected among the set of $\#M \times N$ items avalable. 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 $\#M \times K_M$ 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 $N \to \infty$, we have $s_m \to \sigma$ 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 $\#M \times K$ 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 $N \to \infty$, 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 bandwidth values, from the smallest: $K_M = 1$ to the limit as $K_M \to \infty$.

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.

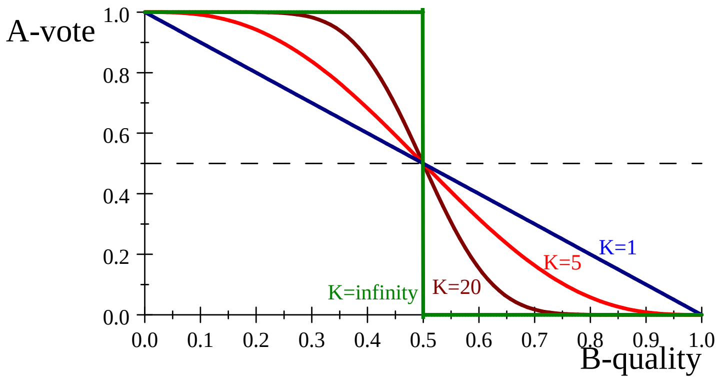


Figure 1: A's vote share in segment as a function of quality σ

4 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

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

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.[8]

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.

It is worth emphasizing one aspect of our analysis. We look at the influence over electoral outcomes of one individual owner. One could imagine that this owner is acting in explicit or tacit concert with other like-minded owners (*the coalition case*) or is acting against other owners who are trying to influence electoral outcomes in the opposite direction (*the opposition case*). Both cases could be analyzed within our approach. In the opposition case, the damage the owner produces is smaller than in our analysis. In fact, the addition of, say, a right-wing biased source in a world of left-leaning sources may improve welfare. In line with our bounds approach, we therefore disregard the opposition case: it is just one possible reason why the upper bound is not reached. The coalition case is instead more relevant. The analysis can easily be extended to encompass sets of like-minded media owners: we simply define the set of biased media sources as those owned by owners in the set.[9] However, of

[8] The analysis assumes that voters divide their attention equally among the news sources they follow. The definition of attention share can be extended to unequal divisions, which can be measured by the time devoted to each source, which in turn is potentially available in practice. This extension is discussed in the conclusion.

[9] For instance, Herman and Chomsky (1988) argued that most US news sources have a built-in bias in favor of a free-market capitalistic ideology. Supporters of that view can identify the set of sources that belong to the 'propaganda system' and use the present model to compute the propaganda system's media power index.

course, defining sets of independent but like-minded media owners is a difficult and subjective task. Instead, ownership is an objective criterion that is already used by regulatory agencies. So, the present paper focuses exclusively on the latter.

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 (see the discussion of Kamenica and Gentzkow 2011 in the literature section.

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 $\min_\beta \beta \times$ [damage given β]. Instead, with incorrect beliefs, the appropriate worst-case notion is simply $\min_\beta$[damage given β]. 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.

A voter who suspects that one of her news sources is biased might react by dropping that source and possibly moving to a different source as a minority of Italian television viewers did when Berlusconi was in power (Durante and Knight 2012). In line with our worst-case approach, this possibility is not considered.

To summarize, our set-up contains a number of assumptions made in a worst-case spirit:

1. The owner is purely partisan;

2. All sources outside G are unbiased;

3. The owner faces no restrictions in his ability to select news;

4. Voters do not observe the number N of news items;

5. Voters do not react to the risk of bias by changing the set of sources they follow. Assumption (5) implies that the media consumption matrix can be taken as

stable, a crucial advantage in the empirical analysis.

Three additional assumptions have been made for analytical convenience:

(a) Voters have homogenous preferences;

(b) There is no abstention;

(c) Voters devote equal attention to all the sources they follow.

These assumptions are not essential to the methodology. All of them can be removed and power indices can be computed through a similar approach. However, if (a), (b), or (c) are removed, the power indices will be computed on the basis of an augmented media consumption matrix, which will have to include information about voters' ideological preferences, abstention rates, and attention patterns, as appropriate. The paper tackles (a) and (b), but not (c). Assumption (a) is discussed in Section 5.1, and the empirical part (Section 6) estimates augmented versions of the power index that deal with (a) and (b). Assumption (c) is discussed in the Conclusion.

We are now ready to analyze the model, with the objective of finding the upper bound to the electoral influence of media organization G. Recall that a voter with bandwith 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^i_k denote the kth 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 $\hat{s}$. Then, the probability of realization $y^i = Y$ would be given by:

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

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*

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

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 (2) 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:

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

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 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 $\beta \to 0$, 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*

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

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.

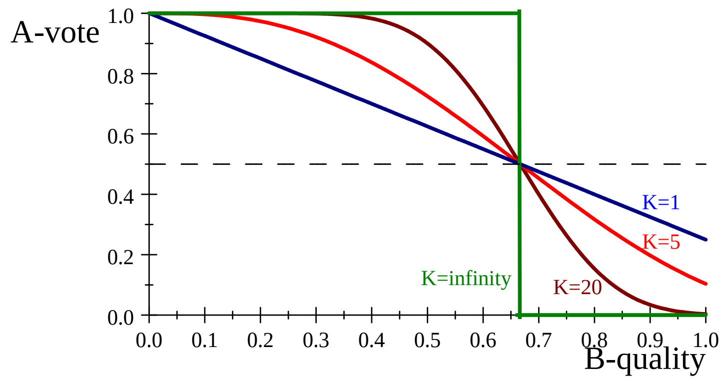


Figure 2: A's vote share in segment as a function of quality σ

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 $K \to \infty$ – 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:[10]

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

[10] We 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

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

If $\sum_{M \subset \mathbb{M}} q_M p_A (g_M, K_M, \bar{\sigma}(K)) \geq 1/2$ 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, which constitutes the main theoretical result of the paper:

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:

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

where median(g_M) is defined as G's attention share for the median voter.[11]

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

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

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

[11] Rank 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.

5 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 $K_M \to \infty$. This means that the upper envelope of A's vote share over K_M is:

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

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 $K_M \to \infty$. 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 $\bar{\sigma}$ be the highest quality of candidate B for which M can still get candidate A elected. This is the same deifinition 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 second 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*

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

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 $K \to \infty$ ($p_A(0,\infty,\sigma)$); 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 $K \to \infty$. The step occurs at $\sigma = 0.5$. This indicates that in a segment with no attention share, if $\sigma > 1/2$ the best case 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).

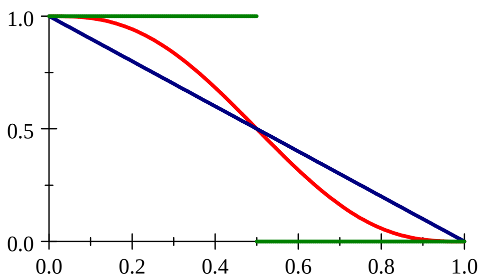
What happens in segments 6 and 10 is more interesting. Website 1 is one of four sources that voters follow: $g_M = 0.25$. The left plot on the second row from top depicts $p_A(0,K_M,\sigma)$ for $K_M = 1, 5$, and ∞. The upper envelope is plotted to the right and it corresponds to $K_M \to \infty$ as 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 that $1/2$ if $\sigma \leq 2/3$. The best case scenario for the evil owner is segments 6 and 10 is $K_M \to \infty$ 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.

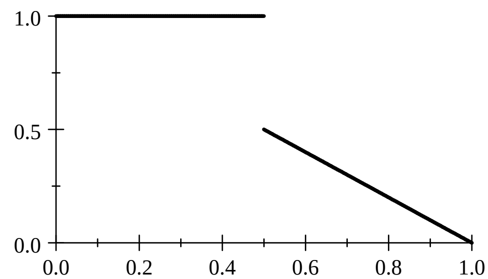
The bottom right plot depicts A's vote share of the total population. It is a weighted average of the upper envelopes obtained for individual segments. The value of $\bar{\sigma}$ is the point where the vote share function is equal to $1/2$, which in this case

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

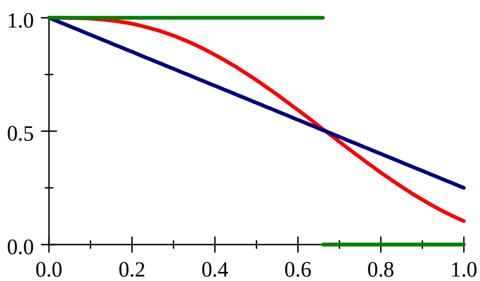
This means that maximal power is achieved when $K_{1-5} = 1$, $K_{6,10} = 1$, and $K_{7-9} \to \infty$. Under these conditions, for any $\sigma < 0.75$, Website 1 succeeds in getting A elected. When σ reaches 0.75, there is no vector of K_M that leads to the election of A.



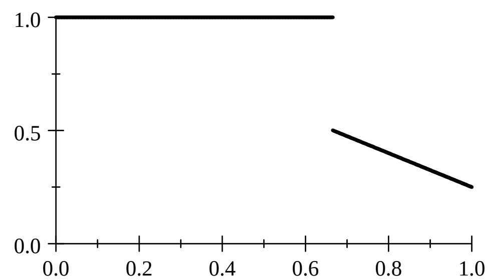
Segment 1-5



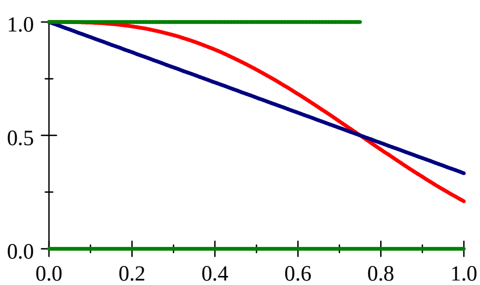
Segment 1-5: Worst Case



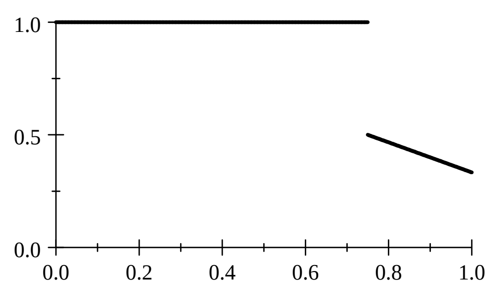
Segments 6 and 10



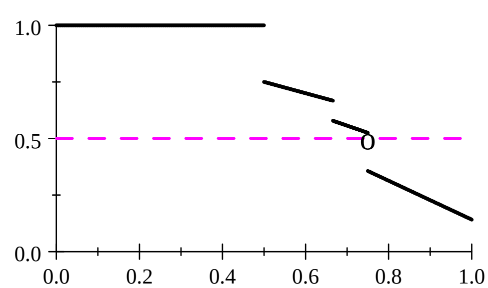
Segments 6 and 10: Worst Case



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 it 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.[12]

5.1 Ideological Voters

While the set of models under consideration is large, one could imagine making it even larger by adding specifications. Some of these possible extensions are mentioned in the Conclusions. Here we discuss one particularly salient one, corresponding to Assumption (a) in Section 3.

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 indeological 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.

While the analysis can be extended to any assumption on the ideological distribution of voters, a particularly tractable case is when voters can be divided in three groups: A-extremists, B-extremists, and moderates. The two extremist groups have the same size. 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. Moderates have no ideological signals. In that case, Proposition 7 applies, as stated, with the proviso that the set of voters is restricted to moderates, as those are the ones who will decide the election. The next section will also report power indices computed under the assumption that US voters can be divided into Democrats, Republicans, and independent voters.

[12] The Stata approximation algorithm is available from the author upon request.

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

6.1 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 included approximately 3000 US residents and included 103 questions.[13]

Questions refer to news consumption only, not entertainment. When covering a generalistic media outlet like CBS, NBC, or ABC, the interviewer asks explictly 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 vists 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 it 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.

[13] As of July 1, 2015, the 2014 edition of the Media Consumption Survey is not yet available for download.

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.[14] 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 some or all of their influence to the original sources would strengthen our conclusion that the power of new media is still limited.

A key decision is to define 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. Figures 4 and 5 represents worst-case power indices $\bar{\Pi}$ for individual news sources and conglomerates, respectively. Figure 6 reports minimal-bandwidth

[14] Still, 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.

power indices $\Pi(1)$. The absolute levels are different – with $\bar{\Pi}$'s being roughtly twice as large as the corresponding $\Pi(1)$'s. However, unlike in the example discussed in the theory section, 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 reports the power index of all daily newspapers except the four that are associated to specific questions: the New York Times, USA Today, the Wall Street Journal, and the Washington Post. The power index of all those dailies corresponds to a (conterfactual) assumption that all of them are under joint ownership. If they were, their power would be roughly equivalent to that of News Corp.[15]

- **Weekly Sources (Tables 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 interent use).

The usage of all major television networks has been monitored since 2004. Figure 11 reports their worst-case power indices from 2002 to 2012. 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.

[15] For the four individually identified dailies (New York Times, USA Today, the Wall Street Journal, and the Washington Post), we have information about both print readers and online readers. For all the other dailies, we have no individual information and we only know print readership. Hence, when we compute the power of dailies without the top-4 and all dailies, only print readers are included.

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.

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, and using the 2010 or 2012 survey.

The results described so far correspond to three of the four main findings of the paper: (1) The three largest conglomerate may wield considerable media power and may individually swing the outcome of almost all presidential elections; (2) Relative rankings are stable across specifications and are dominated by television organizations; (3) As rankings are stable across specifications, the simplest form – the one based on minimal attention $\Pi(1)$, which can be computed analytically from attention shares – is sufficient to predict relative rankings with great accuracy. Results (1) and (2) is a reflection of the high attention share that television commands for the majority of American voters. Other media sources are hampered by the fact that they are followed by fewer people and that those people often have other sources of information. Result (3) is not true because of theoretical reasons: in the example in page 5, the relative ranking according to $\Pi(1)$ is quite different from the ranking according to $\bar{\Pi}$. Result (3) appears to be a feature of the US data.

One can think of many more additional robustness checks or extensions. We discuss four.

6.1.1 Ideology

On important robustness check concerns ideology. As we discussed at the end of Section 5, the model can be extended to an environment with ideological voters. The simplest way of doing this is to assume that there are partisan voters and moderates. At the end of the Pew survey voters are asked to identify as Democrats, Republicans, or Independents. For the purpose of this robustness check, we assume that partisan voters always vote for their party, while moderates decide on the basis of the information they receive. Thus, our model applies as stated after we restrict attention to Independents.[16]

Table 6 reports the media reach statistics and power index values for daily sources

[16] This exercise assumes that the share of Democrats (who vote) is exactly equal to the share of Republicans (who vote), and therefore their weights cancel out in the election. One could add a correction for this difference.

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 a larger number of news sources than partisan voters. Change in the power of an individual source depends on whether the source is more or less likely to be followed by independnet 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). This also applies to 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 Corp gains some ground.

6.1.2 Voter Turnout

The model assumed that that all voters vote – or, equivalently, that the turnout rate is independent of media consumption. In practice, however, different news sources may have followers that are more or less likely to vote. If we knew the turnout probability for each voter, the attention share of each media source would simply be weighted by the turnout probability of followers of that source. One (rough) proxy for the probability of voting is voter registration – one of the questions asked in the Pew Survey. This may provide some information on the direction of the change in media power once we allow for differential turnout rates.

Table 7 presents the new results next to the results for the baseline case. Users of traditional platforms are more likely to be registered voters (a fact we explore in more detail in the age stratification below). The power of television tends to be higher among registered voters than in the overall population, with the notable exception of CNN. New media tend to have lower index values. Newspapers are subject to two effects. The print readersip is higher among registered voters and the digital readership is lower. The new effect on the four newspapers for which we have individual data is ambiguous and close to zero. Instead the effect on print readers overall (captured by "Dailies" and "All Dailies") which excludes online readers is positive.

6.1.3 Age Stratification

Media consumption habits depend on age. Older generations, used to print media, radio, and television, are less likely to consult new media for political information. This may provide some guidance on the direction of the evolution of media power in future years, as the weight of older generations is reduced.

Table 8 shows media power by age. It asks the question: How powerful would the various US media organizations be today if only voters below age T were allowed to vote, where T is set at 30, 40, 50, and 60. As the differences are broadly monotonic in age, Figure 14 zeroes in on the differences between the Under 40's and the whole sample.

A number of patterns emerge. The three traditional networks – CBS, NBC, and ABC – as well as Fox News and MSNBC are much less powerful among younger generations. The only two broadcast media who do better are CNN and NPR. As one would expect, new media fares much better, with Yahoo News in third position and MSN, Google, Facebook, and the Huffington Post gaining ground.[17] Dailies overall are much less popular in younger generations. However, perhaps surprisingly, the two leading national dailies – the New York Times, and the Wall Street Journal – do well. The Times becomes the 7th most powerful source. This is due to their digital readership. Other high-brow news sources, like Bloomberg, Associated Press, and Reuters, also gain ground.

This said, even the dramatic assumption that all US voters over 40 are disenfranchised (the median age of voters is 45) is not enough to revolutionize the US media power landscape. The three media conglomerates still occupy three of the four top spots. While younger generations have different media consumption habits, this effect alone will take decades to subvert the current media power order. The only way for broadcasters to lose their current influence level quickly is if masses of existing viewers decide to switch to other media as sources of political information.

6.1.4 Media Power in State Elections

All the power indices above are computed for the whole of the United States. They measure the influence of media organizations on Federal elections. One may wonder what media sources exert influence in elections for officials elected in a particular state. This question can be answered in a similar way by restricting attention to the set of Media Consumption Interview subjects who reside in the state of interest.This

[17]See the discussion above about the conceptual difficulty in interpreting the power of online sources.

point can be illustrated by looking at New York State.[18] Restrict attention to the fraction of respondents who are New York residents (approximately 7%) and perform the same analysis of Figure 5 on this restricted sample. This produces the power indices for New York reported in Figure 13 together with their US counterparts.

Figure 13 highlights two sets of effects. First, we see that local New York sources have greater index values. The New York Times more than doubles its power and is now the fourth most powerful media organization, behind the three conglomerates. Second, in line with the state's political leaning, we see a shift away from right-leaning media sources. News Corp, which is the most powerful US organization, is now ranked third behind CNN and Comcast. Rush Limbaugh collapses from 0.082 to 0.018. The Wall Street Journal, which arguably is affected positively by the local factor and negatively by the ideological factor has roughly the same power index in New York State and at the national level.[19]

6.2 Calibrated Upper Bounds

In the previous section, we computed the power of media organizations on the basis of theoretical upper bounds. An alternative, which we explore in this section, is to replace those theoretical upper bounds with values obtained from empirical estimates. This approach corresponds to assuming – in a sense that we will formalize below – that the influence of the media on the political process can never be greater than it was in the episodes that gave rise to the empirical estimates.

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. 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

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

[18] The Media Consumption Survey asks detailed questions about local newspapers but does not identify them by name, except for the New York Times, the Washington Post, USA Today, and the Wall Street Journal. Therefore, the only state where we can actually identify two important daily sources is New York.

[19] The state-level power indices must be interpreted with caution. As the media sources in the Pew sample are chosen because they are national in scope, they may provide only limited information on state-level politics. This will underestimate the power of local sources and overestimate the power of national sources.

Thus, the power index is

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

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 $1-b$.[20]

The calibrated upper bounds approach requires an empirical estimate of the power of a particular media organization G That figure, together with the attention share a_G, can be replaced in expression (1) to obtain a value of b, which denotes the share of sophisticated voters that is consistent with the empirical estimate of power. The estimate of b can in turn be used to compute upper bounds to media power for all other organizations. One can also use multiple empirical estimates for different types of media sources. We illustrate the calibration approach with two existing estimates, one for broadcast media and one for the press. We first use one estimate only, and then we add the second one.

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. As Fox News is now available throughout the US, we take the upper bound of that range as the starting point of our calibration exercise. A vote share increase of 0.7 corresponds to a media power of 0.014.[21] Replacing $\Pi = 0.014$ and $a_G = 0.163$, we obtain $b = 0.915$.[22]. This means that a power index of Fox News of 0.014 in 2012 can be rationalized within the model by assuming that 91.5% are sophisticated and the remaining 8.5% are naive.

[20] Again for simplicity, this section restricts attention to the minimal bandwidth case. The analysis could be replicated with the worst-case power definition.

[21] Our media power index is defined over the difference of the vote shares. If there are only two parties – as in our model – a 0.7 percentage points increase for the Republicans must correspond to a 1.4 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.

[22] For the data limitations discussed in the previous section, we do not have a measure of Fox News' attention share in 2000. We therefore compute the b that would rationalize the influence that Fox News had in 2000 in the areas where it was available if it had the same influence in 2012 over the whole country.

On the basis of $b = 0.915$, Table 9 (Column 1) 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 9.24%. Table 7 reports the swing probability thus computed for all major US media.[23]

Let us now use allow for different degrees of naivete among television viewers and newspaper readers. For the latter, we use the influence estimates derived by Gentzkow, Shapiro, and Sinkinson (2011) and Chiang and Knight (2011). The first paper finds a precisely estimated null effect of entry and exit of partisan newspapers on vote shares. This would correspond to $b = 1$ in our calibration. Chiang and Knight (2011) decompose the probabilistic effect of a newspaper's endorsement of political candidate into an informational effect, which depends on the credibility of the newspaper, and a pure "persuasion" effect. They cannot reject the hypothesis that the persuasion effect is zero and all the effect of endorsements comes from information provision. Again, in our calibration, this corresponds to $b = 1$.[24]

The question arises of how to treat individuals who get their news from both the

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[23] Using a different approach, Martin and Yurukoglu (2014) find that a voter who is (exogenously) exposed to an additional four minutes of Fox News is 0.9 percentage points more likely to vote Republican. Take this effect on marginal viewers as the upper bound to the effect on average viewers (29.1% of the audience, spending 1.07 hours/week on Fox News). This means that the total vote share effect is bounded above by 0.14*0.291*1.07, we obtain a power index for Fox News of 0.087, much larger than the one obtained from Della Vigna and Kaplan (2007). This implies $b = 0.18$, meaning that over 80% of voters are naive.

The calibrated estimates would be in the same order of magnitude of the theoretical estimates for minimal attention (see Table 4). For instance, Fox News would have a power index of 0.154 against a theoretical value of 0.202.

[24] The upper bound of Chiang and Knight's (2011) 95% confidence interval is 0.0132, meaning that someone who owned all US media could increase the vote share of his preferred candidate by 1.32% through endorsements (assuming away any informational effect). This translates into a power index of 0.026 for a media monopolist ($G = \mathbb{M}$). The share of sophisticated voters consistent with this value is $b = 0.975$. This means that no more than 2.5% of voters can be naive.

press and television. We explore two scenarios: (A) The same people who are fully sophisticated when they read newspapers may be naive when they watch tv ; (B) Being exposed to written news makes them fully sophisticated even when they watch television. Scenario A is straightforward. Press sources have no power and broadcast sources have the same power as in Column 1.

Scenario B is more complex. Once we exclude Fox News viewers who also access a press source, the attention share of Fox News goes down from 16.3% to 8.0%. This is the attention share we must use to re-compute the sophistication index b to find the value that calibrates Della Vigna and Kaplan's influence estimate. This new value is 0.827, indicating that over 17% of voters who receive news only from television are naive.[25] This higher share of naive voters among pure television users compensates for the fact that all voters that follow both television and press sources are now fully sophisticated.

Column 2 of Table 7 reports the results for Scenario B. By construction, the power of Fox News is the same in Columns (1) and (2) and the power of all press sources is zero. The power of most other broadcast sources is lower because their viewers are more likely to read printed sources than News Fox Viewers, and hence – in scenario B – they would be more likely to undo any attempt to influence them. The only exception is Rush Limbaugh, whose power is slightly higher in this scenario.

Overall, assuming that newspaper readers are fully sophisticated does not upset the relative ranking of the most powerful US media organizations. In a nutshell, this is because the largest media organizations are based on broadcast media and because a large share of their followers do not read newspapers. That insulates most of their audience from information they may learn from the press.

[25] The attention share of Fox News used in Column 1 was $a_{\text{fox}} = 0.163$. The attention share once we drop all Fox News viewers who also get news from the press goes down to $\hat{a}_{\text{fox}} = 0.08019$. The value of the sophistication index $\hat{b}$ that keeps the power index of Fox News constant is given by the solution to :

$$\frac{\left(1-\hat{b}\right)0.08019}{1-\left(1-\hat{b}\right)0.08019} = 0.014,$$

which yields $\hat{b} = 0.827$.

7 Discussion

7.1 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 Newspaper1 and Website1 have expressed an interest in acquiring it. Which of the two buyers poses a larger risk?

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 unknwown, 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.

	merging entities			merged entities	
Segment	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%
$\Pi(1)$	0333	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 (minimal-bandwidth) power index of 0.106. That value would still be lower than the power indices of the three conglomerates: News Corp's 0.221, Comcast's 0.153, and Time Warner's 0.120. Analogously, one could

compute power indices for hypothetical mergers on the basis of calibrated values.

When performing merger analysis, it is necessary to keep in mind the worst-case nature of the present approach. If the merger leads to more similarity between the merging sources, users may react by switching to other sources, thus reducing the influence of the new entity. Durante and Knight (2006) report evidence of this type of reaction among Italian television viewers. The stronger this type of reaction is, the further the actual influence of the merged entity will be from the upper bound computed here.

7.2 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.

The size of these upper bounds supports the criticism by Polo (2005) and others (see introduction) 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, 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 more restrictive upper bounds for every other media organization. As more empirical estimates of media influence become available, furture research can extend and enrich the present model and produce structural estimates of media power.

While this paper considered a large set of possible models, the extension of the set was limited both by the need to have something analytically tractable and by the desire to include only variables that correspond to available observables. Various extensions are desirable.

One may want to develop a finer measure of attention. 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. That information is already available in a rough form in the Pew Survey, given that it allows respondents to qualify the frequency of their time use ("regularly, sometimes, hardly ever, or never").

Furthermore, while the paper included a brief empirical analysis of turnout probabilities, one could imagine a much more thorough study. The model could include the effect of media reporting on turnout and the empirical part could use socio-economic variables to estimate turnout probabilities.

Finally, the current analysis suffers from obvious data limitations. First, it is limited to the United States. The media power index requires a news consumption survey similar to the one run by the Pew Institute. However, a search for similar survey in other countries has been unsuccessful. Second, even within the US, while the Pew Media Consumption Survey is commendable, the quality of the data could be greatly improved, by extending the number of sources studied individually, by collecting precise and validated information on attention (e.g. number of minutes of use), and by linking it to validated socio-economic information. As this information is useful for regulatory purposes, the Federal Communications Commission could spearhead such a data collection effort.

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8 Appendix: Proofs

8.1 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

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

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 $E\left[\sigma|\tilde{Y},\hat{s}\right]$ where $\tilde{Y}$ is Y less a biased signal that was favorable to A and therefore $E\left[\sigma|\tilde{Y},\hat{s}\right]\geq E[\sigma|Y,\hat{s}]=A/B$. 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 miminal 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.

$$\frac{\int_0^1\sigma^{N_1(M/G)}(1-\sigma)^{N_0(M/G)+K_G}\sigma f(\sigma)\,d\sigma}{\int_0^1\sigma^{N_1(M/G)}(1-\sigma)^{N_0(M/G)+K_G}f(\sigma)\,d\sigma}\tag{2}$$

8.2 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 $K_M \to \infty$.

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

$$\left(\begin{array}{c} K_M \\ (K_M - 1)/2 \end{array} \right) = \left(\begin{array}{c} K_M \\ (K_M + 1)/2 \end{array} \right),$$

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 vists 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 though 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 survey groups Associated Press and Reuters. Therefore, their individual power cannot be disentabgle.
- 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. While the four individual newpapers include both print and online readers, "Dailies" and "All Dailies" only include print readers.

Table 3: Daily and Weekly Media Reach

	Share of Followers						
News Source	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

	$\bar{\Pi}$							$\Pi(1)$						
News Source	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. While the four individual newpapers include both print and online readers, "Dailies" and "All Dailies" only include print readers.

Table 5: Power Index of Daily and Weekly Sources

	$\bar{\Pi}$							$\Pi(1)$						
News Source	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. While the four individual newpapers include both print and online readers, "Dailies" and "All Dailies" only include print readers.

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

	Independents			All Voters		
Company	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: Registered Voters (2012, Daily)

	$\overline{\Pi}$		$\Pi(1)$	
Company	Reg	All	Reg	All
AP/Reuters	0.003	0.004	0.001	0.001
Bloomberg	0.006	0.008	0.001	0.002
ABC	0.175	0.170	0.066	0.066
AOL	0.042	0.039	0.014	0.013
BBC	0.013	0.013	0.004	0.004
CBS	0.115	0.111	0.035	0.036
CNN	0.232	0.240	0.081	0.086
Drudge Report	0.021	0.019	0.006	0.006
PBS	0.110	0.102	0.025	0.025
Facebook	0.008	0.011	0.003	0.004
Fox	0.382	0.370	0.199	0.195
Google	0.067	0.071	0.018	0.022
Huffington Post	0.028	0.025	0.007	0.006
MSN	0.121	0.122	0.031	0.033
MSNBC	0.200	0.200	0.066	0.065
NBC	0.217	0.200	0.083	0.077
NPR	0.176	0.170	0.061	0.059
New York Times	0.109	0.101	0.032	0.031
USA Today	0.063	0.060	0.020	0.020
Wall Street Journal	0.072	0.071	0.018	0.018
Washington Post	0.022	0.020	0.005	0.005
Yahoo	0.147	0.162	0.047	0.057
C-SPAN	0.038	0.036	0.008	0.008
Comedy Central	0.078	0.081	0.025	0.028
Rush Limbaugh	0.088	0.082	0.023	0.022
Dailies (w/o NYT, WSJ, USAToday 2010+)	0.436	0.407	0.224	0.214
All Dailies	0.500	0.500	0.280	0.262
Conglomerates				
Time Warner (CNN, Comedy Channel, Time)	0.275	0.286	0.111	0.120
News Corporation (Fox, Wall Street Journal)	0.429	0.419	0.225	0.221
Comcast (NBC, MSNBC)	0.353	0.333	0.161	0.153

Media power indices compute for respondents who report to be registered ("Reg") and all respondents. Everything else is as in Table 4.

Table 8: Media Power by Voter Age (2012, Daily)

	$\overline{\Pi}$					$\Pi(1)$				
Company	< 30	< 40	< 50	< 60	All	< 30	< 40	< 50	< 60	All
AP/Reuters	0.014	0.020	0.012	0.007	0.004	0.006	0.006	0.004	0.002	0.001
Bloomberg	0.014	0.012	0.017	0.010	0.008	0.005	0.004	0.005	0.003	0.002
ABC	0.089	0.085	0.112	0.158	0.170	0.026	0.025	0.037	0.058	0.066
AOL	0.058	0.041	0.039	0.040	0.039	0.018	0.012	0.015	0.013	0.013
BBC	0.043	0.028	0.021	0.013	0.013	0.010	0.006	0.005	0.003	0.004
CBS	0.065	0.050	0.062	0.091	0.111	0.022	0.017	0.022	0.029	0.036
CNN	0.250	0.278	0.283	0.262	0.240	0.105	0.107	0.116	0.105	0.086
Drudge Report	0.007	0.020	0.026	0.019	0.019	0.001	0.005	0.007	0.007	0.006
PBS	0.043	0.028	0.049	0.067	0.102	0.010	0.007	0.012	0.017	0.025
Facebook	0.043	0.041	0.026	0.019	0.011	0.024	0.018	0.011	0.007	0.004
Fox	0.312	0.282	0.321	0.333	0.370	0.159	0.138	0.151	0.160	0.195
Google	0.140	0.129	0.120	0.098	0.071	0.048	0.047	0.041	0.031	0.022
Huffington Post	0.035	0.054	0.044	0.038	0.025	0.007	0.014	0.011	0.010	0.006
MSN	0.164	0.181	0.164	0.153	0.122	0.053	0.056	0.049	0.045	0.033
MSNBC	0.184	0.182	0.170	0.183	0.200	0.063	0.054	0.052	0.057	0.065
NBC	0.125	0.143	0.143	0.170	0.200	0.033	0.044	0.046	0.060	0.077
NPR	0.111	0.197	0.195	0.197	0.170	0.040	0.084	0.076	0.072	0.059
New York Times	0.200	0.167	0.135	0.115	0.101	0.064	0.052	0.043	0.036	0.031
USA Today	0.065	0.076	0.083	0.072	0.060	0.019	0.024	0.027	0.022	0.020
Wall Street Journal	0.114	0.100	0.094	0.081	0.071	0.028	0.028	0.024	0.021	0.018
Washington Post	0.028	0.016	0.024	0.025	0.020	0.009	0.005	0.006	0.007	0.005
Yahoo	0.259	0.250	0.250	0.217	0.162	0.108	0.108	0.102	0.086	0.057
C-SPAN	0.028	0.020	0.029	0.036	0.036	0.006	0.008	0.007	0.008	0.008
Comedy Central	0.215	0.194	0.138	0.107	0.081	0.094	0.077	0.058	0.042	0.028
Rush Limbaugh	0.081	0.076	0.072	0.060	0.082	0.023	0.022	0.021	0.018	0.022
Dailies (w/o NYT, WSJ, USAToday 2010+)	0.205	0.250	0.266	0.333	0.407	0.094	0.107	0.130	0.164	0.214
All Dailies	0.250	0.303	0.333	0.368	0.500	0.126	0.138	0.169	0.205	0.262
Conglomerates										
Time Warner (CNN, Comedy Channel, Time)	0.418	0.412	0.381	0.333	0.286	0.220	0.202	0.189	0.156	0.120
News Corporation (Fox, Wall Street Journal)	0.376	0.338	0.371	0.365	0.419	0.197	0.174	0.183	0.188	0.221
Comcast (NBC, MSNBC)	0.236	0.248	0.250	0.287	0.333	0.101	0.103	0.103	0.124	0.153

The table is constructed like Table 4, except that attention is restricted to respondents strictly below a certain age.

Table 9: Calibration (2012, Daily)

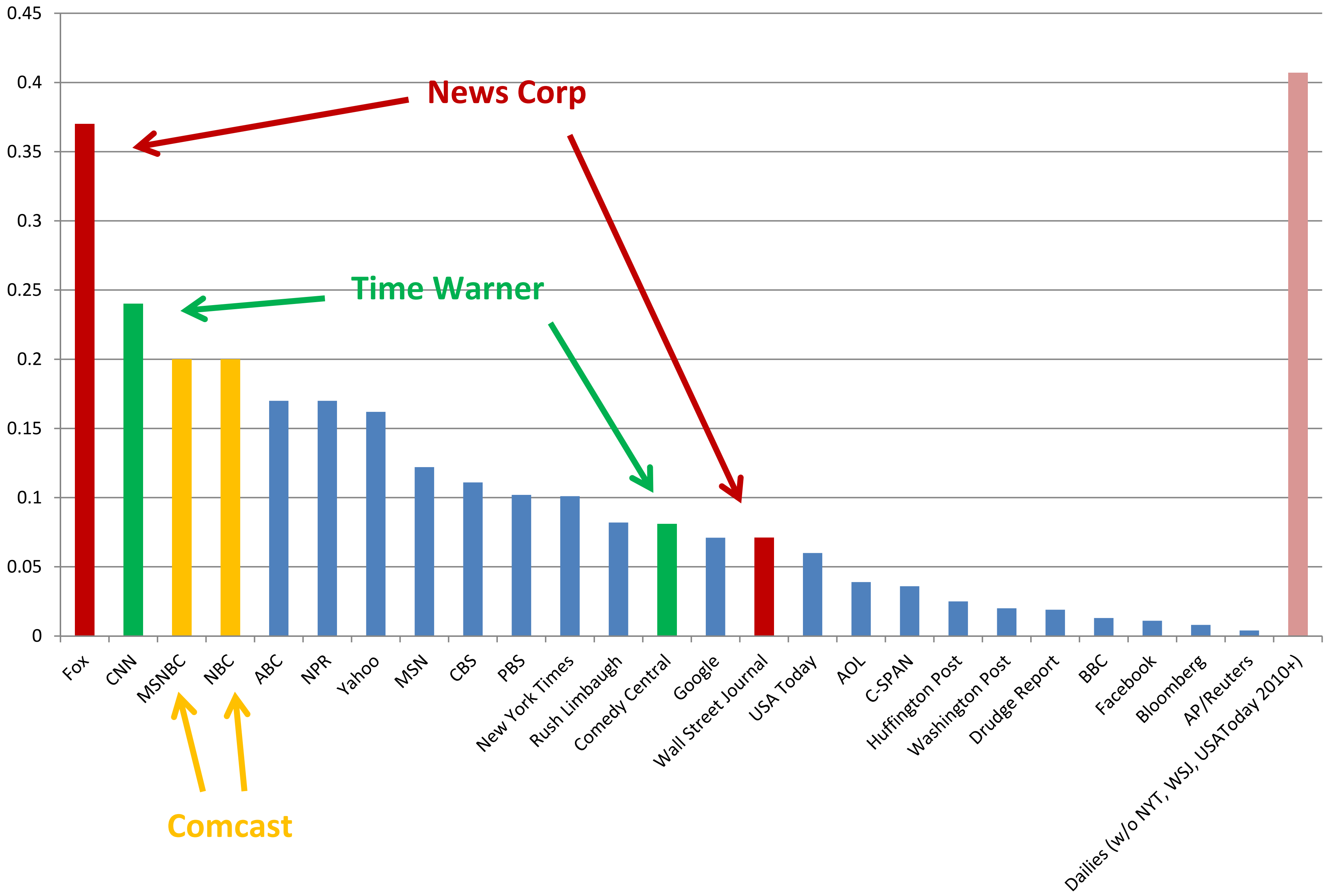
	(1)		(2)	
Company	Π(1)	Swing	Π(1)	Swing
AP/Reuters	0.0001	0.0007		
Bloomberg	0.0002	0.0012		
ABC	0.0053	0.0347	0.0055	0.0362
AOL	0.0011	0.0071		
BBC	0.0003	0.0022	0.0002	0.0010
CBS	0.0029	0.0194	0.0028	0.0186
CNN	0.0068	0.0447	0.0052	0.0341
Drudge Report	0.0005	0.0031		
PBS	0.0020	0.0135	0.0016	0.0103
Facebook	0.0004	0.0024		
Fox	0.0140	0.0924	0.0140	0.0924
Google	0.0018	0.0118		
Huffington Post	0.0005	0.0036		
MSN	0.0027	0.0177	0.0020	0.0134
MSNBC	0.0052	0.0344	0.0034	0.0227
NBC	0.0061	0.0404	0.0047	0.0310
NPR	0.0048	0.0314	0.0039	0.0258
New York Times	0.0025	0.0167		
USA Today	0.0016	0.0108		
Wall Street Journal	0.0015	0.0102		
Washington Post	0.0004	0.0027		
Yahoo	0.0046	0.0303		
C-SPAN	0.0006	0.0042	0.0006	0.0041
Comedy Central	0.0024	0.0155	0.0023	0.0155
Rush Limbaugh	0.0018	0.0120	0.0019	0.0124
Dailies (w/o NYT, WSJ, USAToday 2010+)	0.0152	0.1000		
All Dailies	0.0180	0.1180		
Conglomerates				
Time Warner (CNN, Comedy Channel, Time)	0.0092	0.0604	0.0075	0.0496
News Corporation (Fox, Wall Street Journal)	0.0156	0.1029	0.0140	0.0924
Comcast (NBC, MSNBC)	0.0114	0.0752	0.0082	0.0538

(1): Media power indices are computed under the assumption that 8.5% of voters are naive and $K = 1$.

(2): No newspaper reader is naive; 17.3% of pure television viewers are naive.

Swing Probability is based on the vote share distribution in US Presidential elctions in the last 50 years.

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



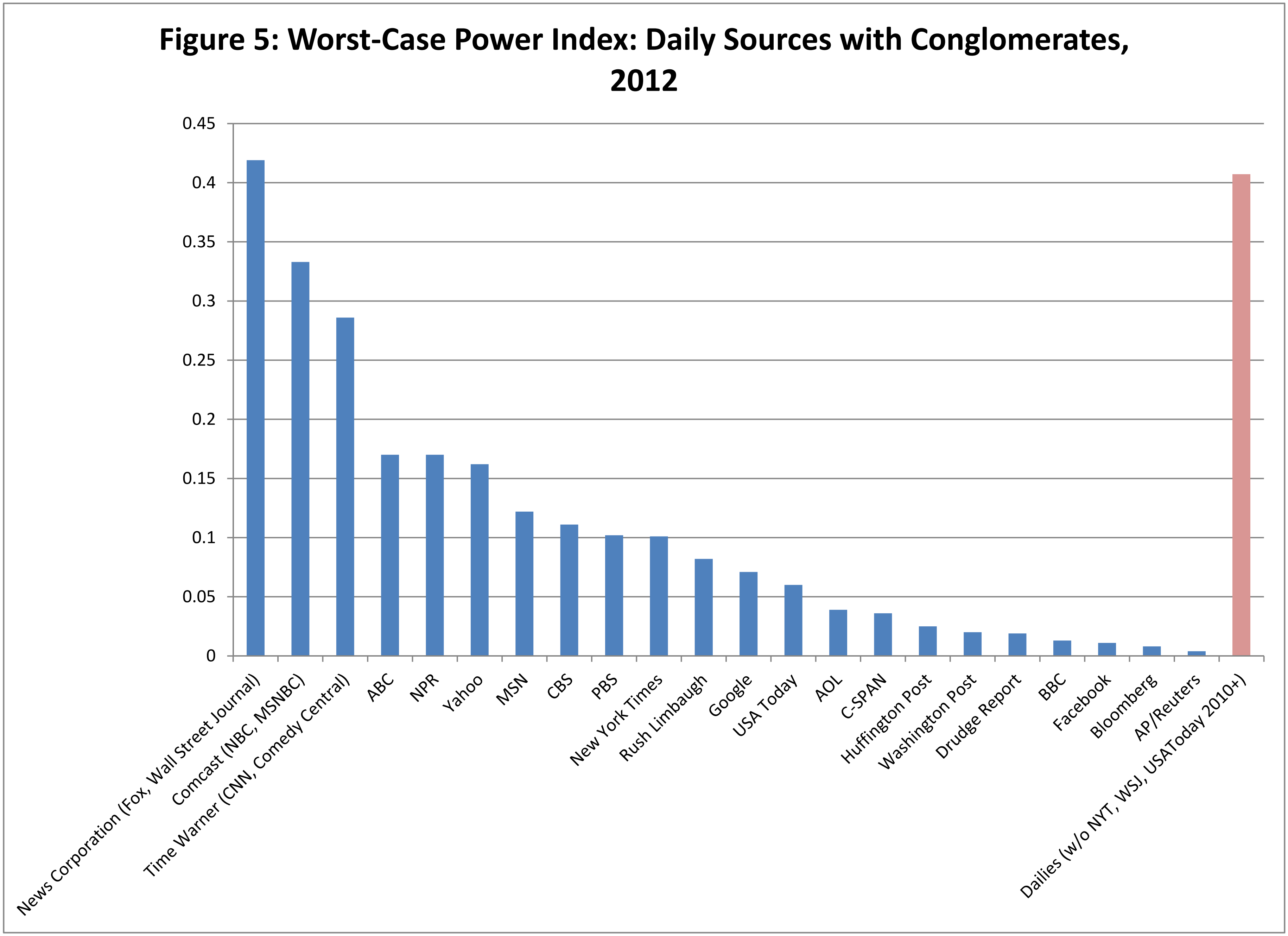


Figure 5: Worst-Case Power Index: Daily Sources with Conglomerates, 2012
0.45
0.4
0.35
0.3
0.25
0.2
0.15
0.1
0.05
0
News Corporation (Fox, Wall Street Journal)
Comcast (NBC, MSNBC)
Time Warner (CNN, Comedy Central)
ABC
NPR
Yahoo
MSN
CBS
PBS
New York Times
Rush Limbaugh
Google
USA Today
AOL
C-SPAN
Huffington Post
Washington Post
Drudge Report
BBC
Facebook
Bloomberg
AP/Reuters
Dailies (w/o NYT, WSJ, USAToday 2010+)

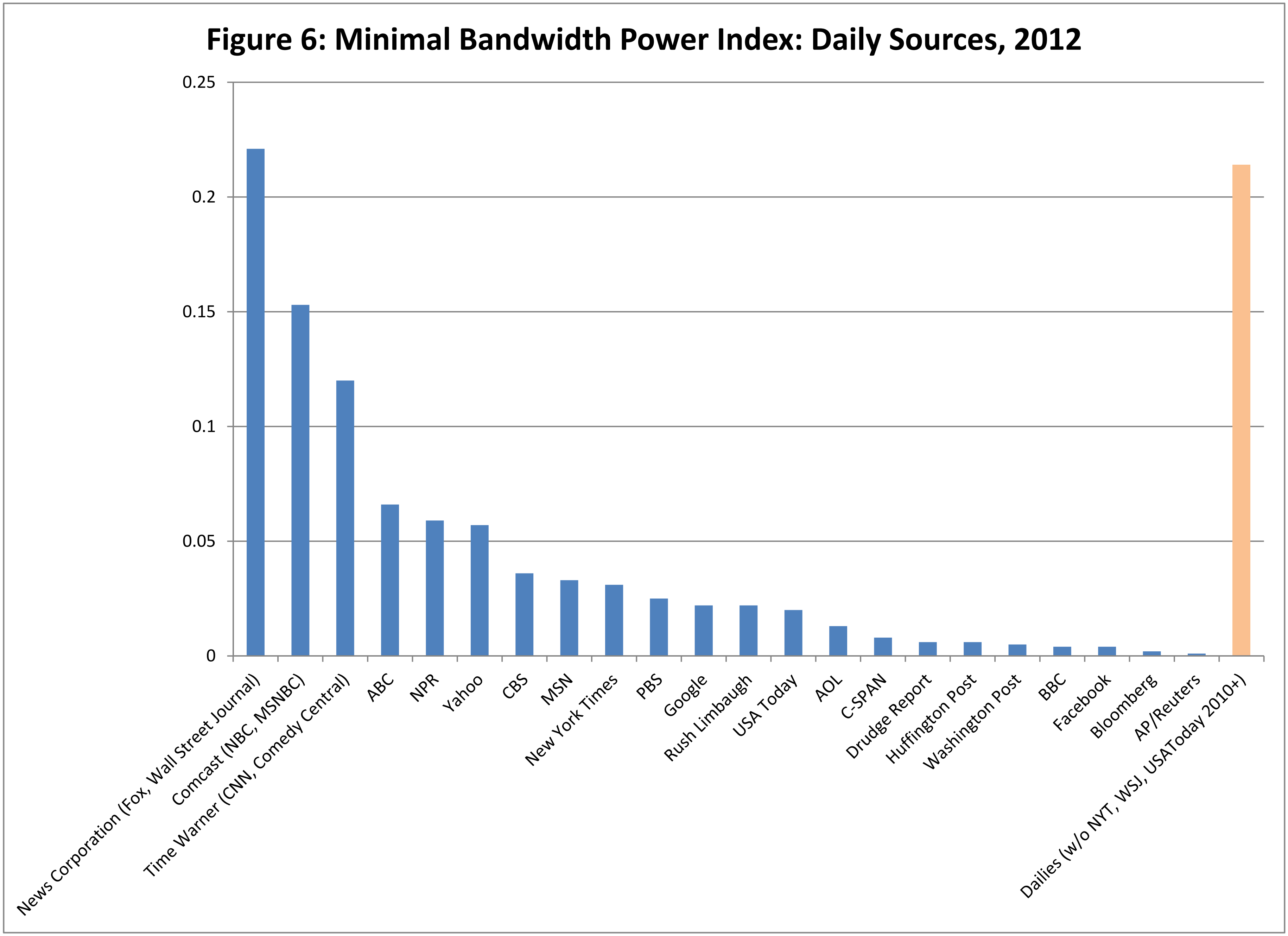


Figure 6: Minimal Bandwidth Power Index: Daily Sources, 2012
0.25
0.2
0.15
0.1
0.05
0
News Corporation (Fox, Wall Street Journal)
Comcast (NBC, MSNBC)
Time Warner (CNN, Comedy Central)
ABC
NPR
Yahoo
CBS
MSN
New York Times
PBS
Google
Rush Limbaugh
USA Today
AOL
C-SPAN
Drudge Report
Huffington Post
Washington Post
BBC
Facebook
Bloomberg
AP/Reuters
Dailies (w/o NYT, WSJ, USAToday 2010+)

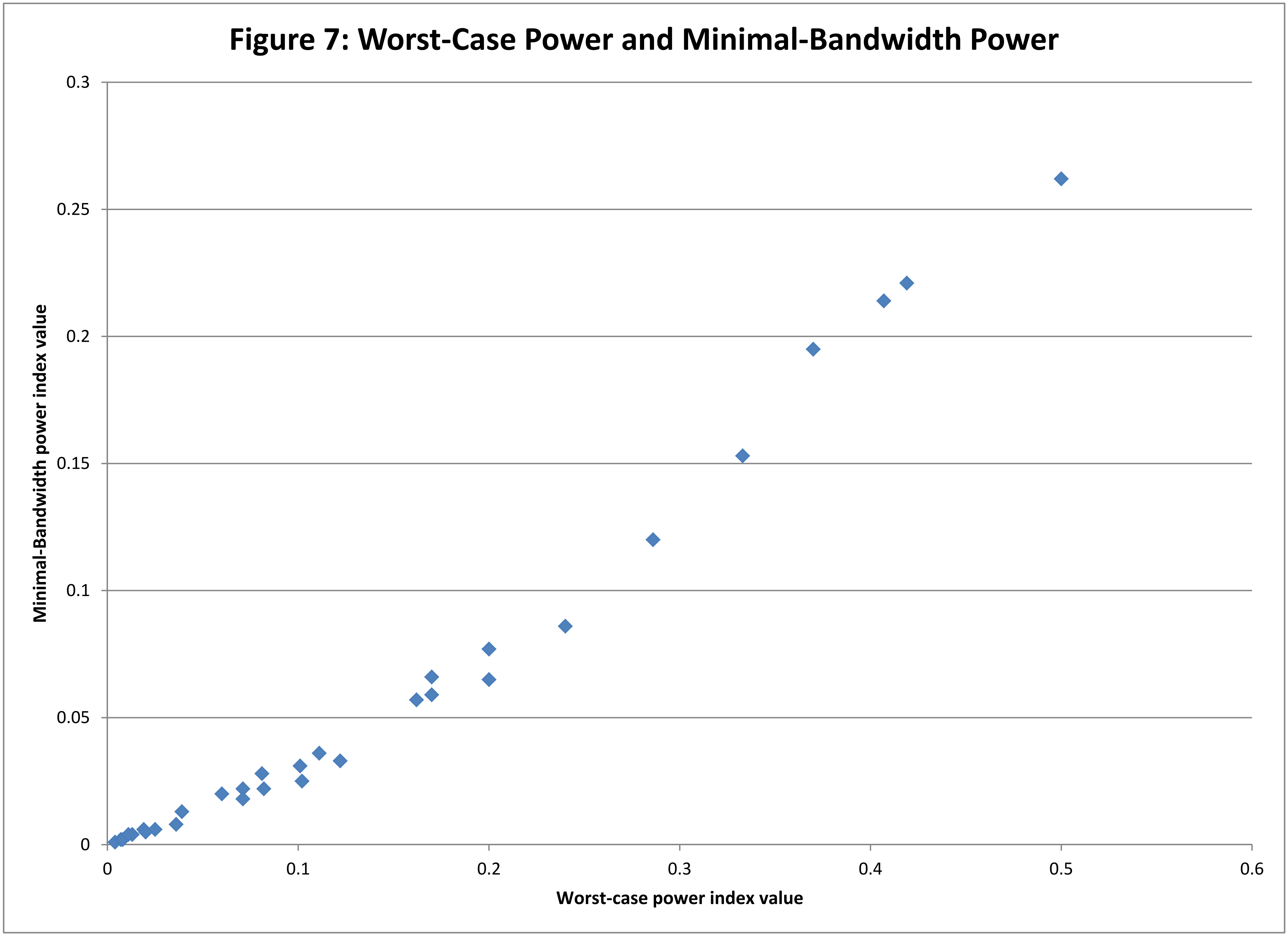


Figure 7: Worst-Case Power and Minimal-Bandwidth Power
Minimal-Bandwidth power index value
Worst-case power index value
0
0.05
0.1
0.15
0.2
0.25
0.3
0
0.1
0.2
0.3
0.4
0.5
0.6

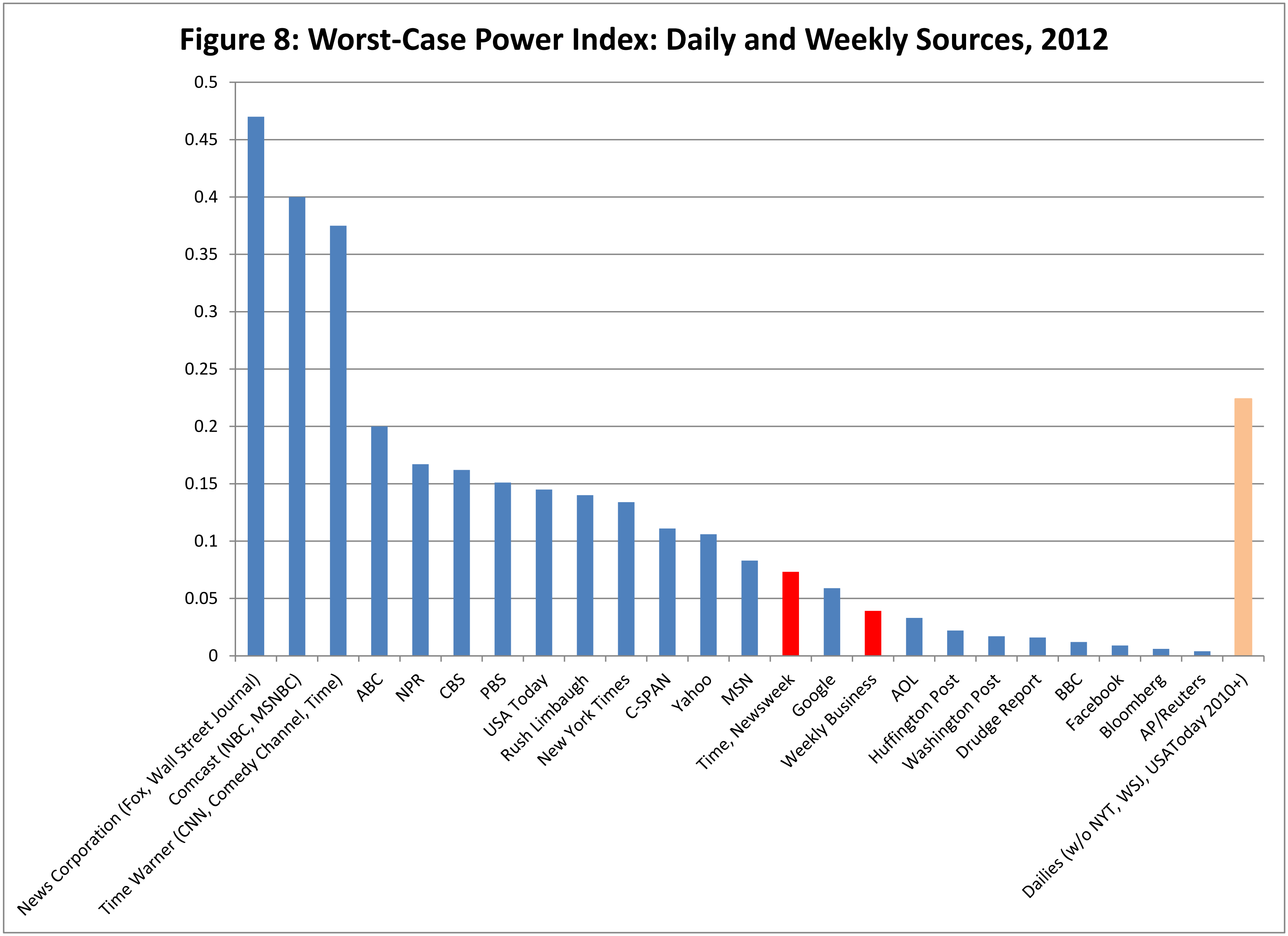
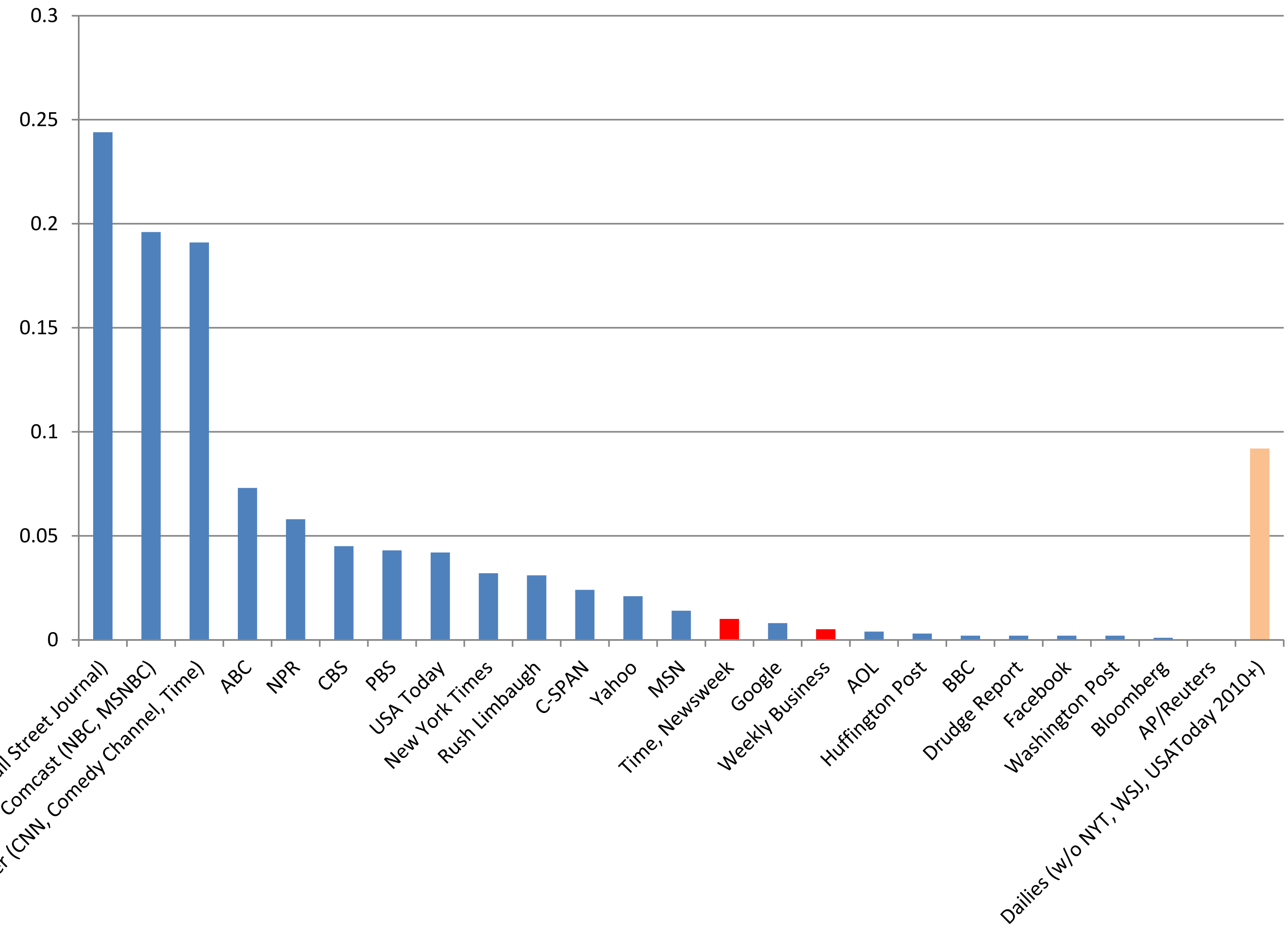


Figure 8: Worst-Case Power Index: Daily and Weekly Sources, 2012
0.5
0.45
0.4
0.35
0.3
0.25
0.2
0.15
0.1
0.05
0
News Corporation (Fox, Wall Street Journal)
Comcast (NBC, MSNBC)
Time Warner (CNN, Comedy Channel, Time)
ABC
NPR
CBS
PBS
USA Today
Rush Limbaugh
New York Times
C-SPAN
Yahoo
MSN
Time, Newsweek
Google
Weekly Business
AOL
Huffington Post
Washington Post
Drudge Report
BBC
Facebook
Bloomberg
AP/Reuters
Dailies (w/o NYT, WSJ, USAToday 2010+)

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



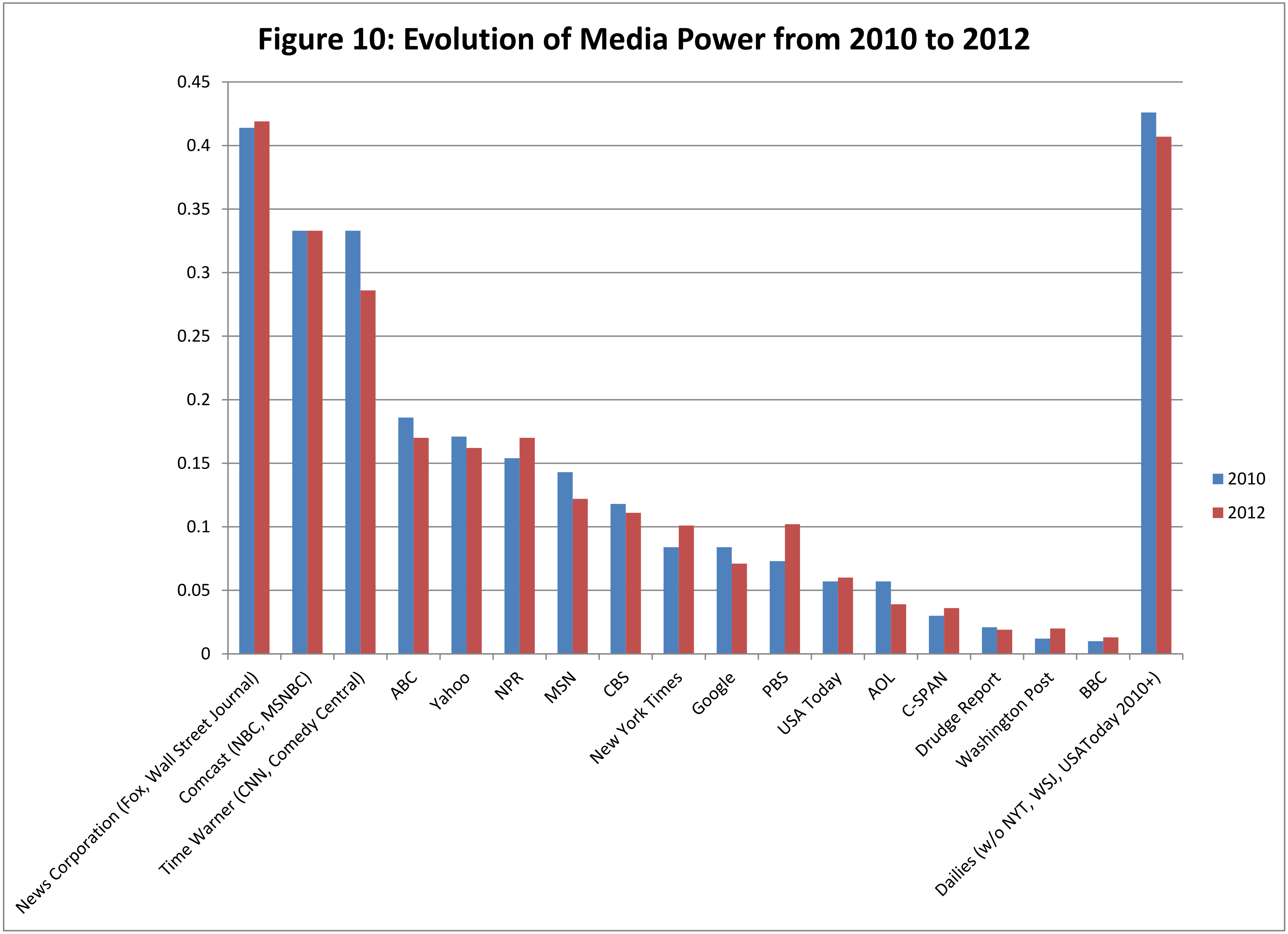


Figure 10: Evolution of Media Power from 2010 to 2012
0.45
0.4
0.35
0.3
0.25
0.2
0.15
0.1
0.05
0
2010
2012
News Corporation (Fox, Wall Street Journal)
Comcast (NBC, MSNBC)
Time Warner (CNN, Comedy Central)
ABC
Yahoo
NPR
MSN
CBS
New York Times
Google
PBS
USA Today
AOL
C-SPAN
Drudge Report
Washington Post
BBC
Dailies (w/o NYT, WSJ, USAToday 2010+)

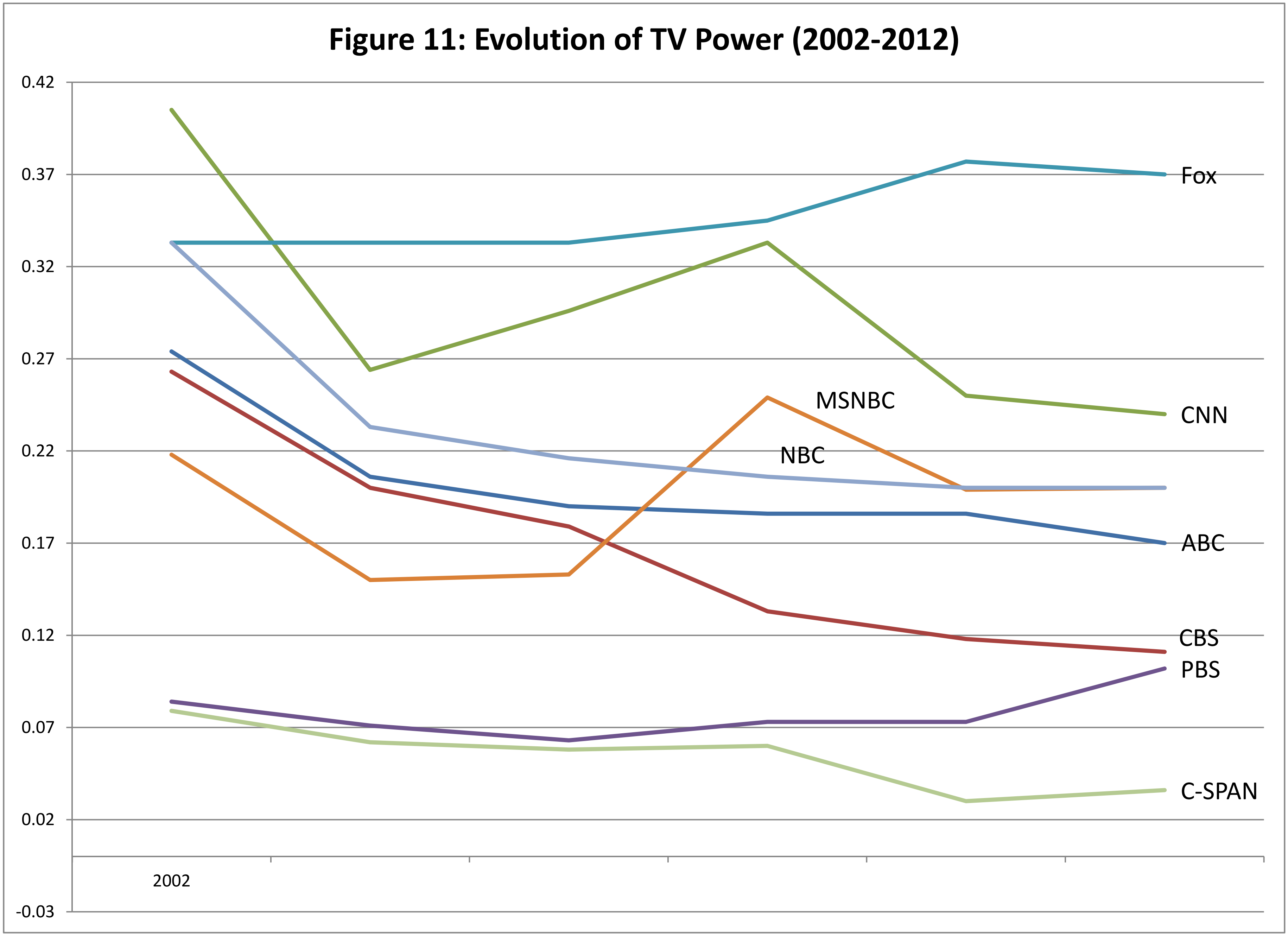


Figure 11: Evolution of TV Power (2002-2012)
0.42
0.37
0.32
0.27
0.22
0.17
0.12
0.07
0.02
-0.03
2002
Fox
CNN
MSNBC
NBC
ABC
CBS
PBS
C-SPAN

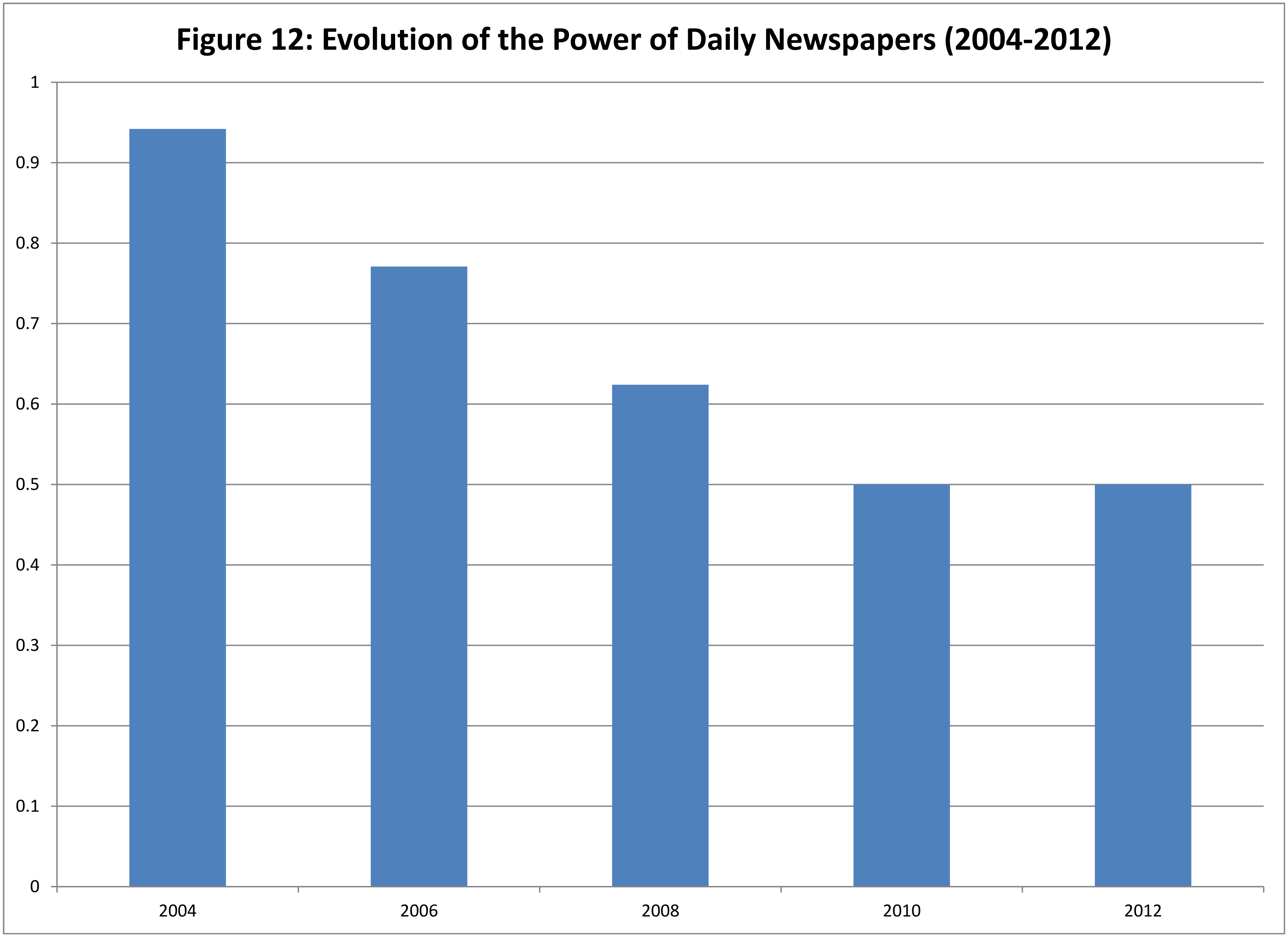


Figure 12: Evolution of the Power of Daily Newspapers (2004-2012)
1
0.9
0.8
0.7
0.6
0.5
0.4
0.3
0.2
0.1
0
2004
2006
2008
2010
2012

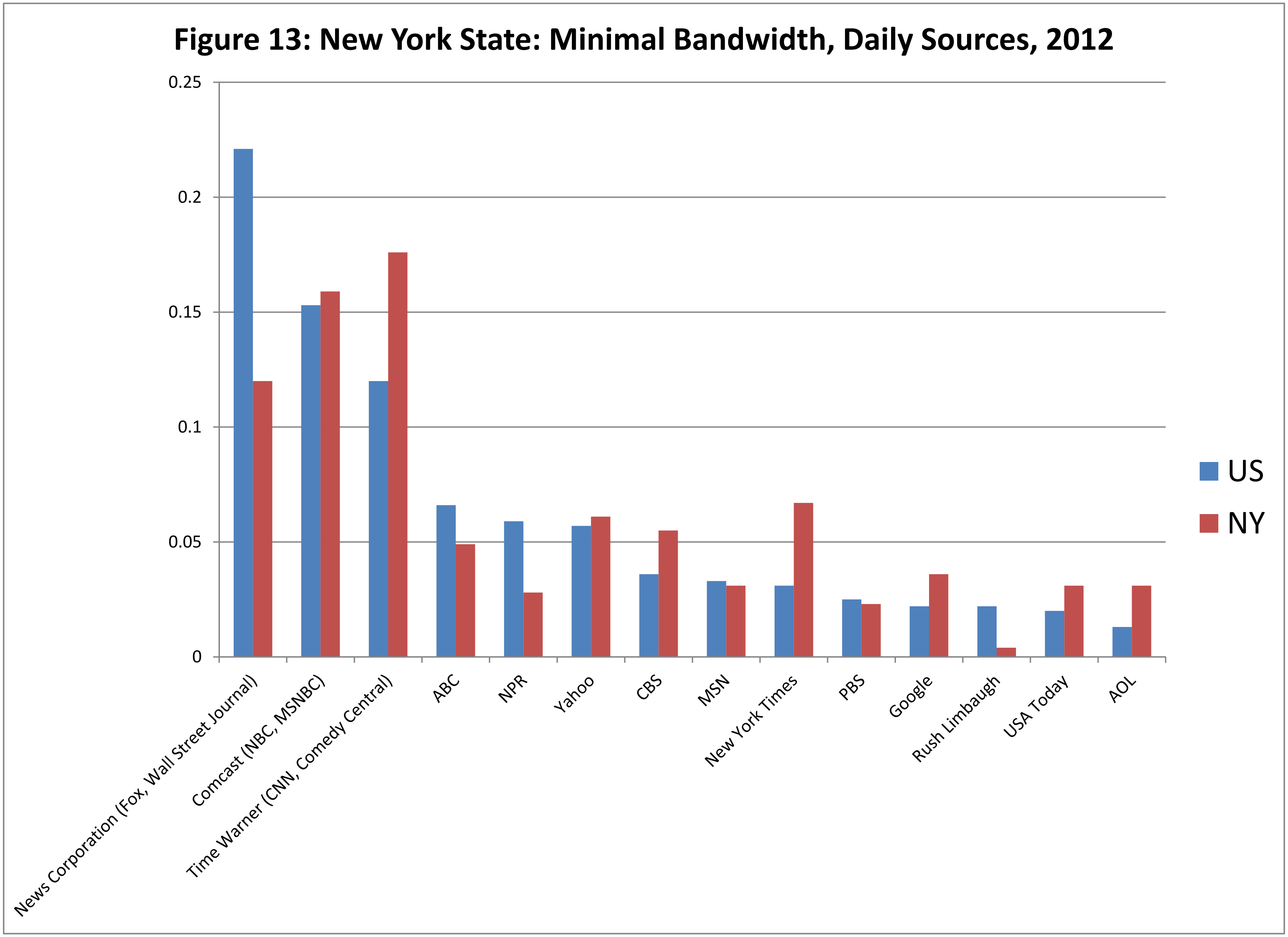


Figure 13: New York State: Minimal Bandwidth, Daily Sources, 2012
0.25
0.2
0.15
0.1
0.05
0
News Corporation (Fox, Wall Street Journal)
Comcast (NBC, MSNBC)
Time Warner (CNN, Comedy Central)
ABC
NPR
Yahoo
CBS
MSN
New York Times
PBS
Google
Rush Limbaugh
USA Today
AOL
US
NY

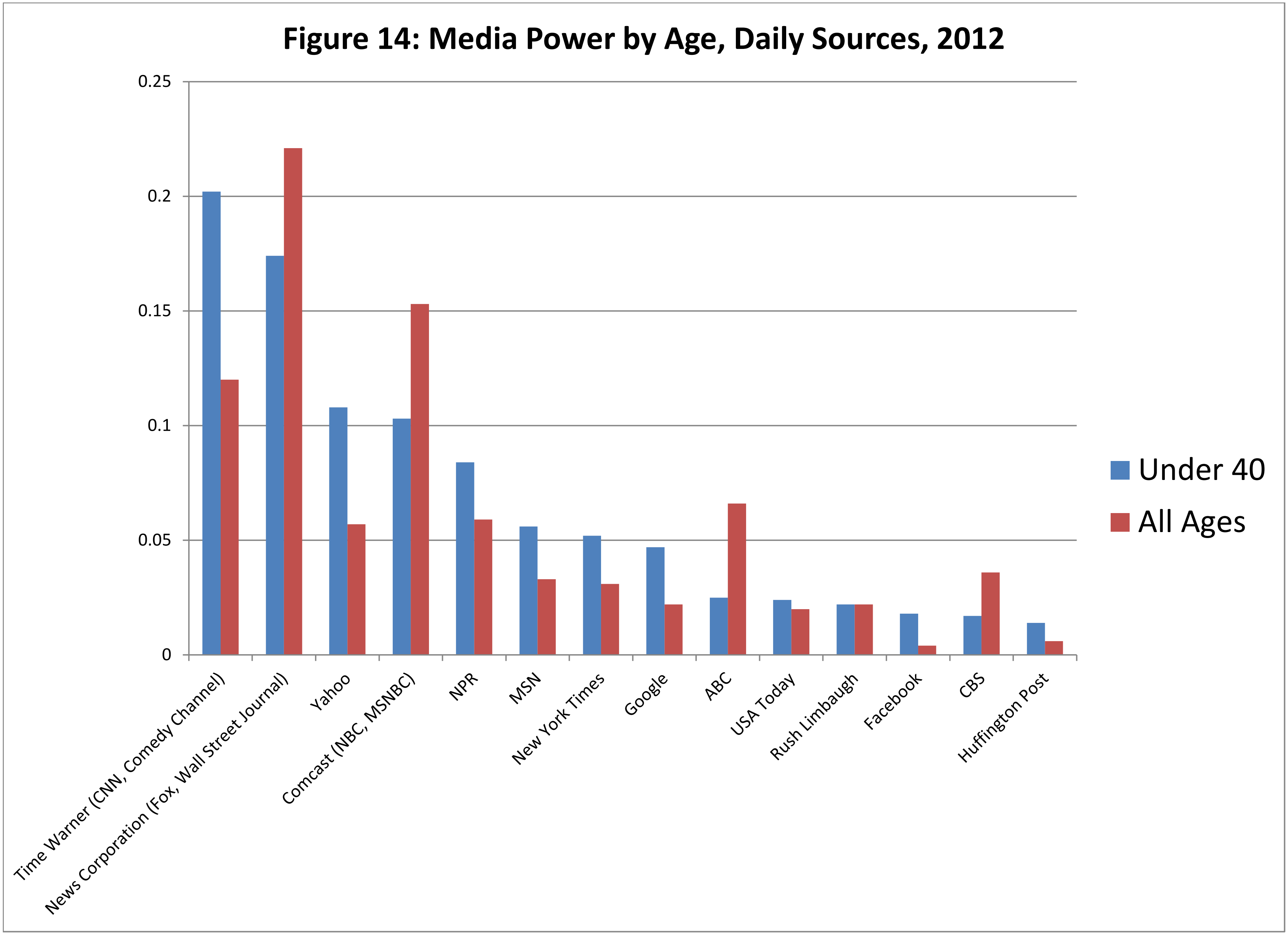


Figure 14: Media Power by Age, Daily Sources, 2012
0.25
0.2
0.15
0.1
0.05
0
Time Warner (CNN, Comedy Channel)
News Corporation (Fox, Wall Street Journal)
Yahoo
Comcast (NBC, MSNBC)
NPR
MSN
New York Times
Google
ABC
USA Today
Rush Limbaugh
Facebook
CBS
Huffington Post
Under 40
All Ages