



Online Institutions, Markets, and Democracy

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TABLE OF CONTENTS

ABSTRACT	vi
ACKNOWLEDGEMENTS	viii
CHAPTER 1: ONLINE GATEKEEPERS AND CASCADE: CONCENTRATION, POLARIZATION, AND DEMOCRACY	
1.1. Introduction	1
1.1.1. Diverse Information, Media, and Democracy	1
1.1.2. Online Information Diversity: Scope & Concept	3
1.2. Competing hypotheses: Quality or Cascade	5
1.3. Data	9
1.3.1. News Readership	9
1.3.2. Politically Extreme Index & Covariates	12
1.4. Results	13
1.4.1. Polarization	13
1.4.2. Online Concentration	19
1.4.3. Do the same newspaper companies consistently benefit from the Internet?	28
1.5. Findings, Discussion, & Conclusion	30
1.6. Appendix	34
1.7. References	35
CHAPTER 2: WHY SHOULD WE EXPECT THE CASCADE TO INCREASE OVER TIME?	
2.1. Introduction	45
2.2. Model	48
2.2.1. Equilibrium	48
2.2.2. Comparative Static	56
2.2.3. Cascading Effect	56
2.3. Welfare Implication	59
2.4. Empirical Evidence	63

2.5. Conclusion & Limitations	71
2.6. Appendix	73
2.7. References	85

**CHAPTER 3: COMPARISONS OF VARIOUS ONLINE INSTITUTIONS
INFORMATION CONSUMPTION ON SOCIAL MEDIA**

3.1. Introduction	89
3.2. Data	91
3.2.1. Online Traffic	91
3.2.2. Twitter Adoption and the Number of “Followers”	93
3.3. Methodology	94
3.3.1. Newspapers’ Social Media Adoption and Online Readership	94
3.3.2. Comparison of Online Traffic Generated by Different Online Institutions	96
3.4. Results	97
3.4.1. Newspapers’ Social Media Adoption and Online Traffic	97
3.4.2. Comparison of Online Traffic Generated by Different Online Institutions	99
3.5. Conclusion & Limitations	101
3.6. References	105

CHAPTER 4: SOCIAL MEDIA, CAMPAIGN FINANCE, AND DEMOCRACY

4.1. Introduction	108
4.1.1. The Recent Adoptions of Social Media in Politics	108
4.1.2. Competing Hypotheses: Minimal vs. Strong Effects	110
4.1.3. Social Media & Political Finance	112
4.1.4. In-states vs. Out-of-states	114
4.2. Data	116
4.2.1. Social Media Activities	116

4.1.2. Campaign Finance	116
4.1.3. Ideological Extremism	117
4.1.3. Additional Data	118
4.3. The Impact of Social Media Adoption on Fundraising	119
4.4.1. Does Social Media Matter in Politics?	119
4.4.2. Does Social Media Create a More Egalitarian Power Structure	124
4.4.3. Do Extremists Benefit More From Social Media?	128
4.4. Robustness Check	130
4.4.1. Cross-sectional Observations	131
4.4.2. Is the Benefit Observable among Top Politicians?	135
4.5. Findings & Political Implications	140
4.6. Limitation & Conclusions	142
4.7. Appendix	144
4.8. References	149

Online Institutions, Markets, and Democracy

ABSTRACT

In this dissertation, I explore the implications of the advances in information and communication technology on democracy. In particular, I examine the roles of online institutions—search engines, news aggregators, and social media—in information readership and political outcomes.

In Chapter 1, I show that information consumption pattern is more concentrated and polarized in online news traffic than in offline newspaper circulation. I then show that this pattern occurs not because online traffic better reflects people's demand, but because online institutions generate a cascade. Using this evidence, I argue that online institutions produce a trade-off between the benefits involved when people access information and the costs of the cascade. In Chapter 3, I compare information consumption pattern on various online institutions.

In Chapter 2, I explain why the cascade may become increasingly significant over time. An increase in Internet users suggests not only a reduced digital divide but also an even more concentrated and polarized online information consumption pattern as, *ceteris paribus*, the magnitude of the cascade will increase with an increase in the number of Internet users. I then empirically show a positive association between the traffic to an online institution and the estimated magnitude of the cascade observed on that site.

In Chapter 4, I show that the observed concentrated and polarized online information consumption may affect political outcomes. For instance, if such an information consumption pattern affects political behaviors, we can expect the same pattern in measurable political outcomes. I test this prediction by investigating the association between U.S. Representatives using Twitter and their fundraising. Evidence suggests that, after politicians started using Twitter, their individual collected contributions became more concentrated, ideologically polarized, and geographically diverse. Finally, I discuss the implications of these findings for political equality, polarization, and democracy.

In sum, online institutions may result in political outcomes becoming more concentrated and polarized. Given that a significant part of the observed concentration and polarization can be attributed to the cascade effect, this paper challenges the notion that Internet-mediated political actions or communications will necessarily promote democracy.

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In retrospect, my academic interests trace back to my questions about the future of capitalism and democracy. Working as a management consultant and a civil servant, I observed a rising economic inequality, increasing political captures by the rising power of large corporations, and threatened political equality, the fundamental premise of democracy. Thus, the questions I had in mind were “why do we observe increasing economic inequality in many developed and developing societies?” and “how can we maintain a separation between economic influence and political equality in order to protect the administrative integrity and the values of democratic procedures?” Although I eventually became interested in the role of media, in terms of protecting the values of our democratic system, my interests have been inherently broad, as the proposed questions suggest. As a consequence, I have been advised by scholars from a wide range of different disciplines, to whom I would like to express my deepest appreciation.

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CHAPTER 1

ONLINE GATEKEEPERS AND CASCADE:

CONCENTRATION, POLARIZATION, AND DEMOCRACY

1.1. INTRODUCTION

1.1.1. DIVERSE INFORMATION, MEDIA, AND DEMOCRACY

A prerequisite for representative democracy is for citizens to vote in their own interests (Dahl 1961). Many democratic theorists¹ contend that exposure to diverse information helps citizens to determine which candidates or policies will best represent their interests (Arendt 1968; Benhabib 1992; Fishkin 1991; Sunstein 2003; Baum 2006) and that it therefore benefits democracy (e.g., Barber 1984; Bellah et al. 1985; Habermas 1989; Mutz & Martin, 2001).² For instance, Zaller states that “public attitudes toward major issues are a response to the relative intensity of competing political communications on those issues” (1992, 210).

In a democracy, the mass media play an important role in enhancing the “relative intensity of competing political communications” by identifying problems in our society and supplying the political information upon which voters base their decisions. In

¹ Some others (for example, Popkin 1993, Lupia and McCubbins, Sniderman, Brody, and Tetlock 1991) have argued that reasoned choice does not require full information.

² Previous research on “groupthink,” a concept first described by Janis (1982), has shown that group deliberation often produces worse decision-making than would be obtained without deliberation. A number of scholars (e.g., Sunstein 2003) have recommended diversity of information as a solution.

particular, the media may, through priming, framing, and agenda setting, influence people's opinions by determining which considerations become the most *salient*, thereby influencing public opinion (Iyenga & Kinder, 1987; Gamson 1992; Iyengar 1991; Nelson & Kinder 1996)³. For instance, most people have multiple considerations that might lead them either to agree with or to oppose most policies (Zaller, 1992; Zaller & Feldman, 1992), and “which of several competing ideas is at the top of a person's head at a particular moment is more than pure accident; it depends on such things as what happened to be in the news that day” (Zaller 1992, 233). Information diversity has become even more important, as the media increasingly focus on controversy and conflict (Bennett 2003; Patterson, 1994, 2000).

Many political scientists and communication scholars have also argued that the Internet is far more *diverse* than traditional forms of media. Scholars have predicted that individuals' increased capacities to share, access, and produce content via the Internet would improve access to diverse information (for example, see Agre 2002; Bennett & Entman 2002) and increase attention to perspectives outside of the mainstream (Castells 2000; Lupia & Sin, 2010). In fact, as many theorists (Benkler 2006; Jenkins 2006) have argued, the Internet has clearly increased access to a greater diversity of political information via new media such as online blogs and social media sites. In these outlets, a broader range of viewpoints are produced and presented by an increasing number of citizen journalists. In fact, Internet-mediated forms of communication have important implications for politics (Farrell 2012).

³ Also see Jacobs & Shapiro 1994, Krosnick & Kinder 1990, McCombs & Shaw 1972, Entman 1993, Gamson & Lasch 1983, Gamson & Modigliani 1987, Nelson, Oxley & Clawson 1997

1.1.2. ONLINE INFORMATION DIVERSITY: SCOPE & CONCEPT

In this study, I explore the effect of the Internet on online information diversity and discuss its political implications. In particular, I argue that the Internet makes information consumption pattern more concentrated and polarized in the online news market because of the cascade created by online gatekeepers.

There are four considerations regarding the scope of this study. First, I examine information diversity here by considering “who speaks and who gets heard as two separate questions” (Hindman 2008, 16), and the discussion is limited to the demand side (information *consumption* patterns), ignoring the supply-side (*availability* of information). Even though the Internet provides a potential platform for everyone, online information *consumption* may not necessarily be more egalitarian than offline consumption.

Second, I conceptualize and consider online information diversity from two different dimensions: *vertical* and *horizontal*. I define vertical diversity as the concentration of online attention for a specific theme or issue, and horizontal diversity as the range of viewpoints, within a specific theme, that receive a certain level of online attention.⁴ Thus, polarization of political information is a particular form of horizontally diverse political information in which viewpoints at the opposite extremes become increasingly popular.

⁴ In other words, we say that the Internet is vertically diverse if online attention and readership is not concentrated on a particular source of information, whereas the Internet is horizontally diverse if a broad range of viewpoints is well represented online.

Third, in this study, I look at diversity of information consumption in a market *as a whole*. Information diversity from the standpoint of individuals may not match the perspective of the market as a whole and may also have differing political implications. With increasingly personalized electronic media (Negroponte 1995, Sunstein 2007), *individual* information consumption may become less horizontally diverse, but relatively little has been discussed about the horizontal diversity of information consumption in a larger online space (e.g., an online news market). For instance, analyzing information consumption in online news markets as a whole can answer whether news with more politically extreme editorial positions is more successful online than offline, which may have significant implications for political polarization.

Fourth, among the various sources of online information, I focus on the online news market. Despite the overwhelming amount of online information available from various sources, most people still trust and rely on the information provided by news organizations (Hargittai 2007, Pew 2011), and the Internet is increasingly becoming a popular platform for online news consumption (Pew 2010).⁵ Accordingly, the online news industry deserves special attention in any investigation of the impact of the Internet on democracy and society.

The remainder of this paper is organized as follows. Section 2 explains the competing hypotheses. Section 3 explains my data. Section 4 describes the empirical framework used for analysis, presents the empirical tests, and discusses their results. Finally, Section

⁵ The Internet as a news platform is already more popular than newspapers, ranking just behind TV (Pew 2010).

5 addresses the implications and conclusions of this study.

1.2. COMPETING HYPOTHESES: QUALITY OR CASCADE

Ever since White (1950) investigated the daily decisions of a newspaper editor, “Mr. Gates,” the concept of news selection by a gatekeeper has been one of the most important theories in political communication and agenda-setting research (McCombs & Shaw, 1972, Baum & Groeling 2008). More recently, many scholars (e.g., Benkler 2006, Williams & Carpini 2000, Hewitt 2005, Trippi 2004) have argued that the Internet’s most important political impact comes from the demise of the influence of these old media gatekeepers. As evidence increasingly suggests (e.g., Hindman 2009), however, new types of gatekeepers have emerged online, remaining a critical factor even in the Internet age. These new online gatekeepers are online institutions or intermediaries—such as search engines, news aggregators, and social media sites—which retrieve, filter, and rank the massive amount of online political information.

Previous studies have identified two possible negative consequences of the Internet and online gatekeepers in politics—*higher concentration* and *polarization*—which I interpret as a decrease in vertical diversity but an increase in horizontal. Hargittai (2000) and Introna and Nissenbaum (2000) were among the first to consider the potential negative impact of search engines on the scope of online information access for the rest of society. Subsequently, some scholars (e.g., Hindman et al. 2003) have provided evidence of the role of online gatekeepers in amplifying the dominance of established

and already-popular websites. Other scholars have also argued that the Internet may change politics for the worse because of its polarizing effect. Putnam (2000) raised the possibility of “cyberapartheid” and “cyberbalkanization.” Sunstein (2001, 2007) contends that the Internet is likely to weaken democracy by creating a fragmented communication market and increasing political polarization. DiMaggio et al. (2001) also suggest that the Internet’s capacity for personalized information sources may heighten the level of extremism. Prior (2007) and Baum and Groeling (2008) show that a greater choice of media outlets has contributed to partisan polarization as people can “self-select” the political information that matches and reinforces their ideological positions.

However, although previous studies have reported some evidence on the role of online gatekeepers in generating more concentrated and polarized online distribution patterns, they have done little to explain *why* this happens. To fill this gap in the literature, I investigate two possible explanations.⁶ The first, the *quality hypothesis*, is that online gatekeepers allow people *consciously* and *voluntarily* to choose the piece of information with *the highest intrinsic quality based on people’s private signals*. Here, I assume that, as in previous studies (e.g. Bikhchandani et al. 1992, and Banerjee 1992), people independently have private information, which is often termed “signals,” about

⁶ The more concentrated and polarized online distribution patterns observed may be explained by three different origins. (1) The supply-side explanation is that because the Internet provides a potential platform for people to publish exceptionally appealing or ideologically extreme ideas online, this increased supply of new types of information concentrates and polarizes online readerships. (2) The demand-side explanation is that the Internet concentrates and polarizes online readerships as it allows people to consume exceptionally appealing or ideologically extreme ideas, which they could have not accessed without the Internet (3) The institutional-side explanation is that online institutions concentrate and polarize online readerships through the gatekeeping process for reasons other than the demand-side factor can explain—for instance, cascading. In this study, I hold the supply-side factor constant, as the sample includes 337 daily newspapers over a relatively short time. The quality hypothesis is related to the demand-side explanation, whereas the cascade hypothesis is related to the institutional explanation.

quality, and I define *quality* as the subjective value of the news information, which might be “either personally useful or merely entertaining” (Zaller, 2003). Thus, I do not assume that soft news is necessarily inaccurate or inferior (Baum, 2003, 2005; Baum and Jamison, 2006). The second explanation, the *cascade*⁷⁸ *hypothesis*, holds that the cascading process makes online traffic more concentrated and polarized as people rely on the information filtered by online gatekeepers *regardless of their private signals concerning the information’s intrinsic quality*.⁹

Several studies (e.g., Hindman et al. 2003) have discussed the role of online gatekeepers in making online attention more concentrated, but few have explained their

⁷ Informational cascade is generally defined as having occurred “if an individual’s action does not depend on his private information signal” (Bikhchandani et al., 1992, p.1000).

⁸ In this study, I define the term “cascade” broadly to describe the different types of cascade that occur with different types of online gatekeepers. Sunstein (2007) uses the term *cybercascade* for that which arises in Internet space and distinguishes between two kinds of cascade: informational and reputational. In the case of the cascade created by search engines, it is difficult to tell whether the resulting cascading process is informational or reputational due to their complicated algorithm. This issue is considered in Barton (2009), in which the cascade in the context of search engines is called “Google cascade.” Barton asserts that “Google cascade” occurs when an individual, having searched for something on Google, follows the behavior of the Google results without regard to his own information. Barton contends that Google cascade exhibits the characteristics of both information and reputation cascades, as Google’s algorithm is based on both the *number* of sites that link to the particular site in question and the relative *popularity* or *reputation* of the linking sites (see also Pasquale 2006, Lastowka 2007, Grimmelmann 2009; see Sunstein 2007 for the definition of reputational cascade; See Google.com, Technology Overview, <http://www.Google.com/corporate/tech.html> for information on Google’s algorithm.)

⁹ In addition to the cascade, previous studies (e.g., Bikhchandani et al. 1992) have suggested alternative primary mechanisms for uniform social behavior including (1) sanctions on deviants, (2) network effect with positive payoff externalities, (3) conformity preference, and (4) communication. In order to rule out these alternative explanations, I later introduce a common example in which Google’s algorithm can create herd behavior. Suppose that I want to hyperlink the term “federalism” on my website. Therefore, I search for the term with Google, click through to the first result, and hyperlink it after a quick confirmation that the content matches with what I have in mind. As this heuristic example suggests, search engines or other online media institutions may create herding, as people often decide which sites to link or click by seeing the site that search engines or other media institutions rank first (or one of the first few). In this example, herd behavior may arise even without any sanctions enforced or the positive externalities that may result from selecting the first search result. Moreover, the resulting herd behavior in the example may arise even without people’s inherent wish to conform to the behavior of others and lacking any communication about the benefits of the sites. In fact, as this example suggests, herd behavior arises in many cases as people tend to use the most vivid or convenient piece of information as a benchmark when they collect information, even when this information is not appropriate (Jervis, 1993; Tversky and Kahneman, 1973).

potential role in polarizing political information. Online gatekeepers can help people “self-select” ideologically extreme information and polarize information consumption in at least two ways. According to the quality hypothesis, online gatekeepers help people read politically extreme ideas online, to which people have wanted access but previously could not without the Internet because of the high cost of access.¹⁰ On the other hand, according to the cascade hypothesis, all else being equal, online gatekeepers tend to more easily identify, and thus rank higher, the more *salient* information. Farrell and Drezner (2008) find that online focal points allow “interesting” opinions—for instance, new or neglected issues—to rise to the “top” of the blogosphere and be more easily identified by online gatekeepers. Obviously, convincing and well-argued facts and arguments are “interesting,” but another way not to be overlooked by online gatekeepers is to post unique stories that not many people have discussed before—for instance, politically extreme viewpoints.

In this study, I argue that online gatekeepers concentrate and polarize people's information consumption patterns mainly through cascade. Although both the quality and cascade hypotheses may lead to the same outcome, their implications for democracy and social welfare differ if we assume that typical individuals prefer—all else being equal—more accurate and socially desirable information, and that their private signals are correct, on average. According to the quality hypothesis, the observed winner-take-all distribution pattern occurs because online gatekeepers help people find the information

¹⁰ For example, suppose that a person in Massachusetts had wanted to read a radically conservative newspaper before the Internet was introduced, but he could not because the type of newspaper he was looking for was not published in Massachusetts. With the Internet, however, he can search for and compare different newspapers and choose to visit them regularly.

with the best quality—the most accurate and socially desirable—out of a massive amount of online information. This process might then improve social welfare and deliberation for democracy. On the other hand, according to the cascade hypothesis, there is a trade-off between low-cost information access and cascade; online gatekeepers allow people to access new information at lower costs, but this benefit comes at the cost of a significant cascade. With this tradeoff, the Internet will not necessarily improve either social welfare or deliberation for democracy.

Thus, this study answers three different sets of questions. (1) I test whether online news consumption is more concentrated online than offline and whether news from sources with politically extreme editorial positions commands more attention online than offline. (2) I report the empirical association between the role of online gatekeepers and the observed concentration and polarization of information consumption in the online news market. (3) I present empirical evidence that leads to supporting the cascade hypothesis and rejecting the quality hypothesis.

1.3. DATA

1.3.1. NEWS READERSHIP

The newspaper industry is one of the few industries in which reliable data is available for both online and offline readerships of relatively identical products. Newspaper companies usually publish the same articles in their printed and online versions, and we can collect reliable data across the entire industry regarding offline subscriptions to

newspapers and the numbers of unique visitors to newspapers' websites. In this paper, I define online and offline readerships by the market shares of their audiences, as follows.

$$ShareUV_{it} = \frac{Unique\ visitors_{it}}{\sum_j Unique\ visitors_{jt}}$$

$$ShareCirc_{it} = \frac{Paid\ Circulation_{it}}{\sum_j Circulation_{jt}}$$

The online readership of newspaper i is the share of unique visitors to the website of this newspaper out of the total of unique visitors to all websites of U.S. daily newspapers. The offline readership of newspaper i is the share of average circulation of this newspaper out of the total average circulation of all U.S. daily newspapers.

I created a data set of online and offline readerships for 337 daily newspapers. This number includes nearly all major U.S. newspapers except for community newspapers and those that do not have their own websites.¹¹ In the analysis, I did not include newspapers whose unique visitor information could not be found. The average circulations of the U.S. daily newspapers were taken from the Audit Bureau of Circulation, and they cover two six-month periods: April 1, 2010, to September 30, 2010, and October 1, 2010, to March 31, 2011. I purchased the data for online unique visitors from Compete, Inc., to cover the period from April 1, 2010, to March 31, 2011.

¹¹ For example, some newspapers in Michigan were excluded because they share a website (www.mlive.com) and do not maintain individual websites.

Based on the sites that people use before visiting a given newspaper website, I disaggregated the data describing the number of monthly online unique visitors into *direct traffic* and *referred traffic*. *Direct traffic* refers to the online traffic that is not referred by any other websites (e.g., when a person types *www.nytimes.com* directly into the web address bar and visits the *New York Times* website). *Referred traffic* can be further disaggregated depending on the site that referred the traffic (e.g., *search engine traffic*, *news aggregator traffic*, and *social media traffic*).

One difficulty of grouping online traffic in the above manner is the possible ambiguity between *search engine traffic* and *direct traffic*. For example, certain individuals type the name of a specific newspaper into the Google search engine in order to visit the newspaper's website. In this case, the traffic, though not different from *direct traffic*, would be classified as *search engine traffic*. To avoid this problem, I collected data on the keywords that people used to reach a given newspaper website and reclassified this traffic from *search engine traffic* to *direct traffic* if the keywords were variants of the name of each newspaper. For example, to visit the *New York Times* website, some people directly typed keywords related to the name of the paper, such as *new york times*, *nytimes*, or *nyt*. I reclassified the traffic that was generated from these searches (i.e., *name search traffic*) from *search engine traffic* to *direct traffic*.

Another difficulty arose because of paid search, an advertising strategy wherein website owners pay a fee to have their website displayed more prominently in search engine results. As the share of paid search is generally too small to affect the results of

this analysis¹² and because paid searches are not a focus for this study, I subtracted the volume of paid search traffic from *search engine traffic*.

1.3.2. POLITICALLY EXTREME INDEX & COVARIATES

Another important variable of interest is newspapers' editorial positions in terms of political ideology. As newspapers' ideological positions are unobservable, I follow previous studies (e.g., Chiang and Knight 2012) in using the average political preferences of people who self-report to read the newspapers as a proxy. This variable comes from 2008 National Annenberg Election Surveys (NAES) conducted by the Annenberg Public Policy Center at the University of Pennsylvania. The survey asked respondents which newspaper they read most regularly and inquired after their self-reported political ideology from 1 (extremely liberal) to 7 (extremely conservative). I first subtracted 4 from this individual ideology score and took its absolute value so that 0 means moderate and a positive number means more politically extreme (either conservative or liberal). Then, for each news outlet i , I defined an absolute extremism index by taking the average of the score from individuals who answered that they read newspaper i most regularly, and then transforming the values logarithmically in order to interpret coefficients as percentage differences. Among the 337 daily newspapers in our sample, this index was

¹² The data provided by Compete, Inc., show that paid searches account for only 0.6 percent of the total traffic to newspaper websites.

available for 335 outlets.¹³ To be specific, newspaper i 's extreme index is as follows, where subscript r is a respondent and i is a news outlet.

$$extreme_i = \ln\{average(|ideology_{r,i} - 4|)\}$$

I also generated indicator variables for newspapers that either instituted a paywall or provided specialized content news. Only two (the *Wall Street Journal* and *Long Island Newsday*) have a paywall, and three (*American Banker*, *Investor's Business Daily*, and *Women's Wear Daily*) are classified as a specialized newspaper. I did not classify the *Wall Street Journal* as a specialized newspaper so that the specialized news indicator coefficient would reflect how online readership might change as small newspapers specialize their content.

1.4. RESULTS

1.4.1. POLARIZATION

To see the role that gatekeepers play in online concentration and polarization, I first looked at evidence of polarization with the following regression. The dependent variable is the log-transformed share of online readership, and the variable of interest is newspaper i 's politically extreme index, $extreme_{it}$.

¹³ For a small subset of my sample, I was able to obtain the slant index developed by Gentzkow and Shapiro (2010). The correlation between the average ideology variable developed above and the slant index was positive and statistically significant (p-value < 0.01).

$$ShareUV_{it} = \alpha_0 + \beta \text{extreme}_i + \gamma \text{ShareCirc}_{it} + X_i + \alpha_t + \varepsilon_{it} \quad (1)$$

The set of covariates X_i includes whether newspaper i has a paywall or provides contents specialized for business news. I also include time-fixed effect α_t and control for the share of offline circulation to estimate the extreme editorial positions on online readership, holding constant the offline readership levels. In this equation, a positive coefficient β implies that, all else being equal, newspapers with more ideologically extreme positions have a higher readership online.

I then test the empirical association between the role of online gatekeepers and the estimated coefficients β by replacing the dependent variable $ShareUV_{it}$ with the share of online readership generated by different gatekeepers: *direct traffic*, *search engine traffic*, *news aggregator traffic*, and *social media traffic*. Specifically, (1) *if the quality hypothesis is true*—that is, if the polarization occurs as people consciously and voluntarily try to find extreme content on the Internet—coefficient β should be significant when I use $ShareUV_{it}$ with *direct traffic* as the dependent variable. On the other hand, (2) *if the cascade hypothesis is true*—that is, if people rely on the information filtered by online gatekeepers, regardless of their private signals, and if online gatekeepers tend to amplify the salience of extreme content—coefficient β should be more significant, both statistically and substantially, when I use $ShareUV_{it}$ with *search engine traffic*, *news aggregator traffic*, and *social media traffic* compared to when I use it with *direct traffic*. The key assumption is that *direct traffic*—the online traffic generated

by typing the site address directly into the web address bar—better reflects people’s true preferences based on their private signals concerning quality, than does referred traffic.

Table 1.1 shows the estimated results. First, column 1 in Table 1.1 shows a positive association between the extreme index and total online readership. This evidence suggests that news from sources with politically extreme editorial positions gain more attention online than offline. Second, column 2 in Table 1.1 allows us to reject the quality hypothesis. As explained, if the quality hypothesis were true, column 2 should have produced a significantly positive association between the extreme index and *direct traffic* as in column 1. However, as can be seen in column 2, the extremism premium is no longer observed if we look at only the *direct traffic*. Third, columns 3–5 imply that online gatekeepers play a role in amplifying the salience of extreme ideas as they show that the extreme index is positively associated with *search*, *aggregators*, and *social media traffic*, respectively. These results suggest that *search*, *aggregators*, and *social media traffic*, rather than the *direct traffic*, are driving the positive association observed in column 1, which leads us to reject the quality hypothesis and support the cascade hypothesis.

In sum, this result implies that online gatekeepers *do* help information from ideologically extreme sources to gain popularity. *Ceteris paribus*, news sites with the most politically extreme positions generate online traffic that is 8 percent higher than traffic for those with the average extreme index.¹⁴ The partial scatter plots shown in Figure 1.1 give a visual sense of the coefficients of the extreme index in Table 1.1. The

¹⁴ The maximum extreme index is 3, whereas its mean value is 0.72. A 320 percent increase in the index is associated with about an 8 percent increase in online traffic.

fitted lines with linear parametric assumptions have significantly positive slopes, both statistically and substantially, when the vertical axes are $ShareUV_{it}$ with *search engine traffic*, *news aggregator traffic*, and *social media traffic* (Figures 1.1.2, 1.1.3, and 1.1.4), but not with *direct traffic* (Figure 1.1.1).¹⁵

¹⁵ Further, these partial scatter plots show another important point missing in Table 1.1; the extreme group of news organizations—for instance, the group with an extreme index value above 1.5—has a higher share of online readerships even when we use *direct traffic* (Figure 1.1.1). This point is more obvious if we fit the data with a non-parametric assumption (for instance, with Kernel-weighted local polynomial smoothing). In sum, with regard to the extreme group of news organizations, I could not reject both the quality and cascade hypothesis. However, except for those in the highly extreme group, the estimated results support only the cascade hypothesis.

Table 1.1: Test of the Role of Online Gatekeepers on Polarization

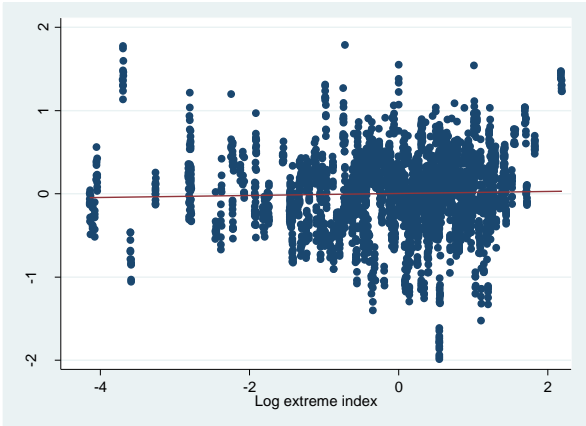
	(1)	(2)	(3)	(4)	(5)
	Dependent variable is $ShareUV_{it}$ constructed by				
	Total UV	Direct Traffic	Search Traffic	News Aggregators Traffic	Social Media traffic
$extreme_i$	0.024* (0.010)	0.001 (0.009)	0.036** (0.010)	0.028** (0.010)	0.039** (0.011)
$paywall_i$	-0.630** (0.054)	-0.651** (0.048)	-0.789** (0.074)	-1.002** (0.083)	-0.316** (0.054)
$specialized_i$	0.524** (0.106)	0.559** (0.105)	0.147 (0.106)	-0.829** (0.105)	-0.580** (0.107)
$ShareCirc_{it}$	1.161** (0.011)	0.992** (0.012)	1.271** (0.014)	1.188** (0.014)	0.999** (0.015)
N	3826	3473	3473	3473	3473
adj. R^2	0.797	0.750	0.734	0.692	0.602

Note:

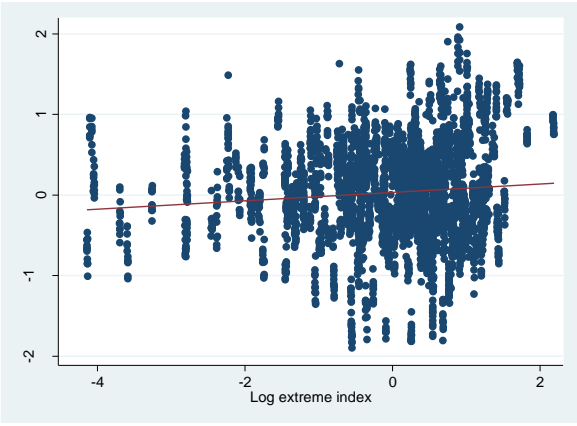
1. Standard errors in parentheses, * $p < 0.05$, ** $p < 0.01$
2. All specifications use time fixed effects

FIGURE 1.1: Direct Traffic vs. Offline Circulation

1.1.1 Direct Traffic vs. Extreme Index



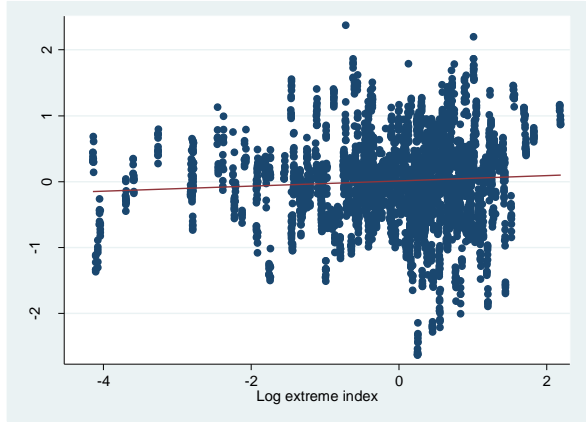
1.1.2 Search Traffic vs. Extreme Index



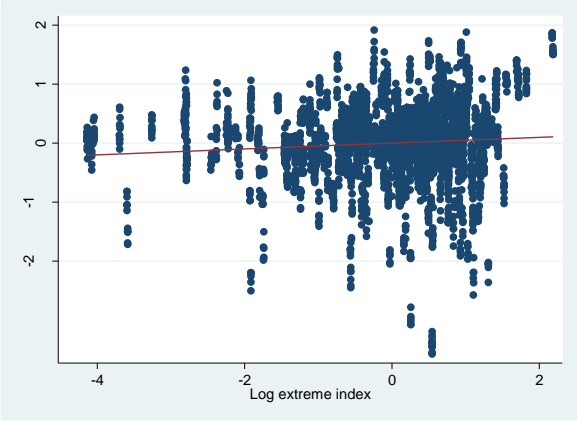
Note:

Partial scatter plot of log share of online readership against log extreme index (based on Table 1.1; the axes represent components orthogonal to other regressors.)

1.1.3 News Aggregators Traffic vs. Extreme Index



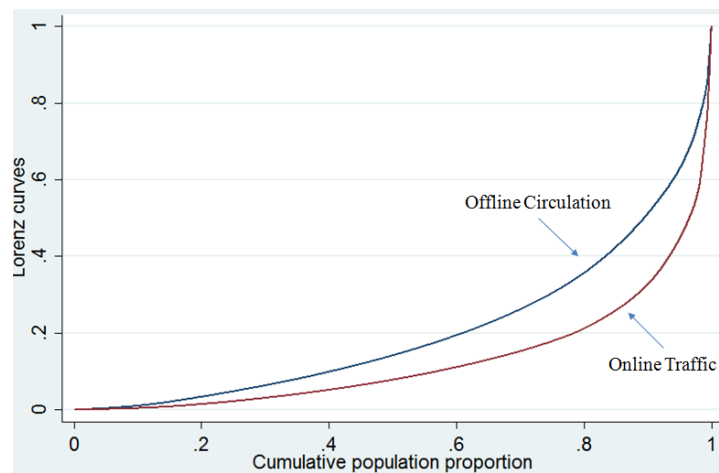
1.1.4 Social Media Traffic vs. Extreme Index



1.4.2. ONLINE CONCENTRATION

I conducted two different analyses for testing online concentration. First, to see whether readership is more concentrated online than offline, I plotted Lorenz curves¹⁶ for the distributions of both online and offline readerships and conducted Kolmogorov-Smirnov (K-S) tests. Second, to see whether higher online concentration has something to do with online gatekeepers and whether the data supports either the cascade or the quality hypothesis, I ran quantile regressions.

FIGURE 1.2: Online Traffic vs. Offline Circulation



The estimated Lorenz curves and the K-S tests show clearly that the readership is more concentrated online than offline. Figure 1.2 plots Lorenz curves for online and offline readerships and shows that the top 10 percent of newspapers attract about 50

¹⁶ A graphical representation of the cumulative distribution function of the empirical probability distribution. Every point on the curve represents a statement, such as “The bottom x percent of all newspapers have y percent of the total readerships.”

percent of the total offline readership but almost 70 percent of the total online readership. The results of the K-S tests (Table 1.2) clearly reject the null hypothesis that the distributions of online and offline readerships are equal.

Table 1.2: Two-sample Kolmogorov-Smirnov tests for Equality of the Two Distributions:

Online Traffic vs. Offline Circulation

Smaller Group	Coefficient D	P-value	Corrected
Offline circulation	0.0121	0.562	
Online traffic	-0.3044	0.000	
Combined Kolmogorov-Smirnov Test	0.3044	0.000	0.000

Then, to explore the association between the observed online concentration and gatekeepers, I ran the following quantile regression:¹⁷

$$Share_{it} = \beta_{\theta} Online_i + \gamma extreme_i + X_i + \alpha_t + \varepsilon_{it} \quad (2)$$

$Share_i$ is the log-transformed readership of newspaper i , and $Online_i$ is an indicator variable that is 1 if the readership of newspaper i is online and 0 if offline. The other

¹⁷ An alternative way to conduct this test is to see whether the association between $ShareCirc_{it}$ and $ShareUV_{it}$ is nonlinear and whether it increases in $ShareCirc_{it}$. However, there are two reasons for conducting quantile regression instead of ordinary least squares (OLS). First, as I discuss in this study, the higher online concentration is driven by only a small number of outliers (the top 4–5 news organizations), and quantile regression is a better tool for observing this impact than OLS, as OLS tests the mean impact with a parametric assumption. Second, quantile regression tells us the impact on *distributions*, not on individual newspapers. Thus, even if a news outlet with high circulation did not have an increase in share of online traffic, it might still be true that outlets in the top quantile have a higher share of readership online than offline. (See Angrist and Pischke 2008, p. 281, for further information on this subtle difference).

variables are as defined in equation 1. The coefficient β_θ is the estimated difference between online and offline readerships at quantile θ . For example, if $\beta_{\theta=1\%}$ were 3 percent, the online readership of the top 1 percent of newspapers would be 3 percent higher than the offline readership of the top 1 percent of newspapers.

FIGURE 1.3: Online Traffic vs. Offline Circulation

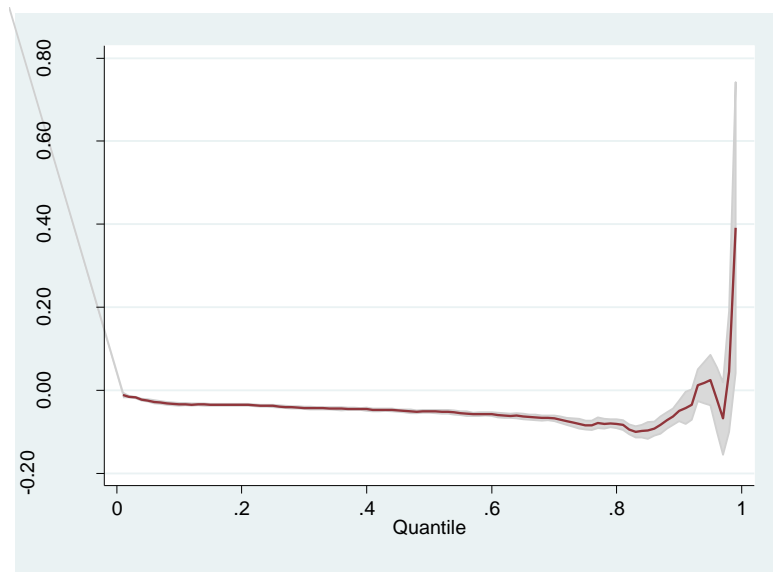


Table 1.4 reports the estimated quantile regression coefficients, and Figures 1.3 and 1.4 plot the estimated coefficients β_θ of equation (1) at each quantile θ with a 95 percent confidence interval.¹⁸ As presented in column (1) of Table 1.4, the online readership of the topmost newspapers is, on average, 39 percent higher than that of the offline ones. This result is driven by a small number of national newspapers; Table 1.3 shows the differences in the offline and online readerships of five news organizations, the

¹⁸ See Koenker and Hallock (2001) for applied examples of quantile regression analysis.

largest in terms of circulation. During the data collection period, four out of the five biggest newspapers—except for *The Wall Street Journal*, which maintained a paywall during observations—had a significantly higher readership online than offline.¹⁹ The online and offline readerships of small²⁰ newspapers differ little in terms of magnitude, but the online readership for the middle group was about 4–7 percent lower than its offline readership, which is consistent with prior research that reports a “missing middle” (Hindman 2008).

I then use disaggregated online traffic (*direct traffic*, *search engine traffic*, *news aggregator traffic*, and *social media traffic*) in place of the online readership for the dependent variable to test the role of online gatekeepers. Specifically, (1) *if the quality hypothesis is true*, $\beta_{\theta=99\%}$ will be significant when I use *direct traffic* for the dependent variable. On the other hand, (2) *if the cascade hypothesis is true*, I expect that the observed dominance of topmost news organizations, estimated by $\beta_{\theta=99\%}$, will be more significant, both statistically and substantially, when I use *search engine traffic*, *news aggregator traffic*, and *social media traffic*, as opposed to using *direct traffic* for the dependent variable.

Column 2 in Table 1.4 and Figure 1.4 allows us to reject the quality hypothesis. As explained, if the quality hypothesis were true, replacing the dependent variable with the readerships constructed by *direct traffic* should have resulted in estimates similar to that

¹⁹ This finding is expected, given that *The Wall Street Journal* was the only newspaper company that instituted a paywall between April 2010 and March 2011, requiring individuals to pay a fee in order to access a large percentage of the newspaper’s stories.

²⁰ The bottom 10 percent in terms of readership

in Figure 1.3. This is because *direct traffic* may be regarded as a proxy for what the total traffic would have been without online gatekeepers (Hong 2012). However, the two results (Figures 1.3 and 1.4.1) look completely different, with the top newspapers having no higher readerships online than offline in Figure 1.4.1, although the coefficients were not significant.

Columns 3–5 in Table 1.4 support the cascade hypothesis. In the case of *search engine traffic*, top newspapers hold about an 88 percent higher readership online than offline. I found similar results by constructing online readerships with *news aggregator traffic* (e.g., *Yahoo! News* or the *Drudge Report*) and *social media traffic* (e.g., Facebook and Twitter).

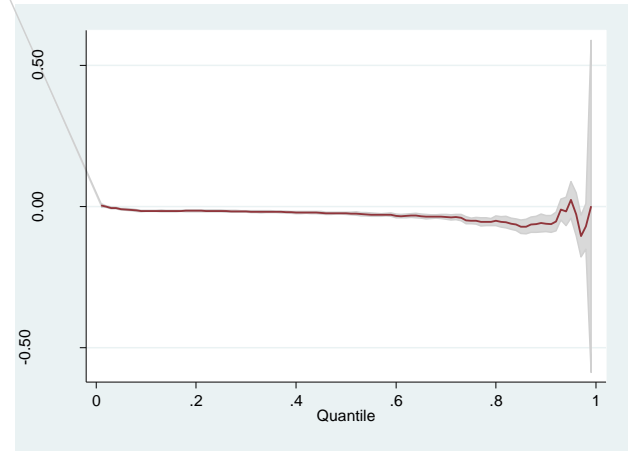
Table 1.4: Test of the Role of Online Gatekeepers on Concentration

Quantile	(1)	(2)	(3)	(4)	(5)
	Dependent variable is $Share_{it}$ constructed by				
	Total UV vs. Circulation	Direct Traffic vs. Circulation	Search Traffic vs. Circulation	Aggregators Traffic vs. Circulation	Social Media traffic vs. Circulation
99%	0.392** (0.088)	0.001 (0.066)	0.882** (0.166)	0.424** (0.061)	0.346** (0.084)
90%	-0.049** (0.021)	-0.061** (0.017)	0.014** (0.035)	-0.037 (0.026)	-0.022 (0.017)
70%	-0.068** (0.005)	-0.037** (0.003)	-0.070** (0.003)	-0.045** (0.003)	-0.028** (0.007)
50%	-0.051** (0.002)	-0.024** (0.002)	-0.052** (0.002)	-0.041** (0.002)	-0.017** (0.003)
30%	-0.042** (0.002)	-0.017** (0.002)	-0.048** (0.002)	-0.045** (0.002)	-0.019** (0.003)
10%	-0.033** (0.001)	-0.016** (0.001)	-0.040** (0.001)	-0.035** (0.001)	-0.024** (0.002)
<i>N</i>	7853	7429	7433	7445	7445

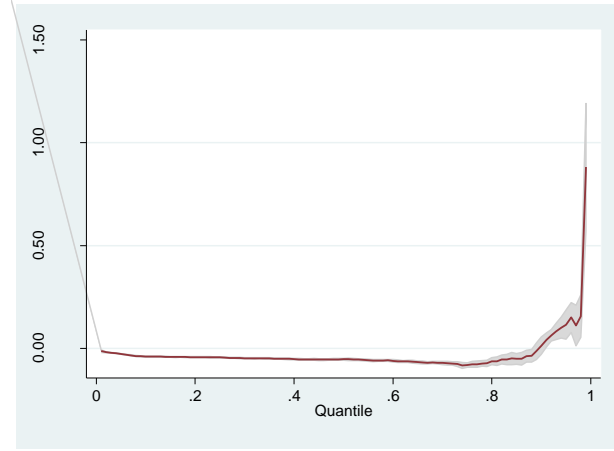
Note: 1. Standard errors in parentheses, * $p < 0.05$, ** $p < 0.01$
 2. All specifications use time fixed effects
 3. Standard errors are bootstrapped.

FIGURE 1.4: Direct Traffic vs. Offline Circulation

1.4.1 Direct Traffic vs. Offline Circulation



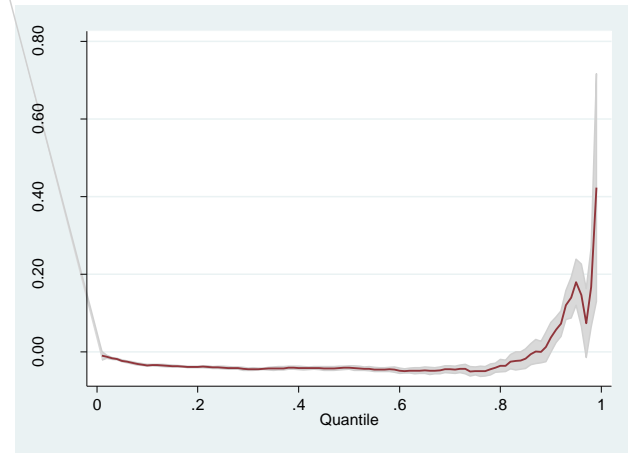
1.4.2 Search Traffic vs. Offline Circulation



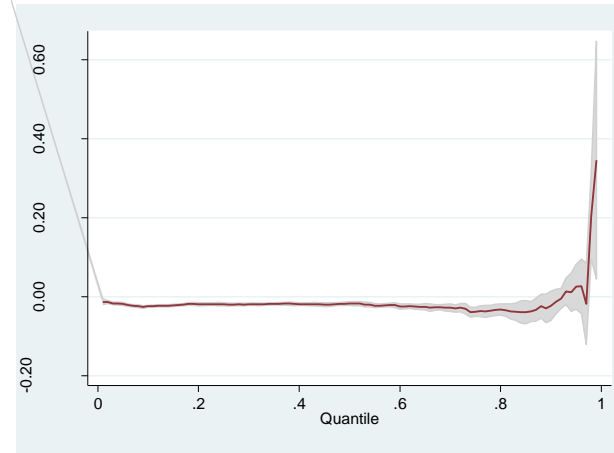
Note:

1. The gray area is the confidence interval
2. See Koenker and Hallock (2001) for examples of graphical analysis using quantile regression analysis.

1.4.3 News Aggregators Traffic vs. Offline Circulation



1.4.4 Social Media Traffic vs. Offline Circulation



Figures 1.5 and 1.6 show additional evidence that relates to and further supports these findings. Figure 1.5 plots the proportion of the *direct traffic* of total online unique visitors against the rank in terms of total online traffic. This graph suggests that most of the online traffic received by top news websites is referred by online gatekeepers, whereas small newspapers receive a significant portion of their online traffic directly. Figure 1.6 indicates a similar finding. People use search engines to visit both well-known and smaller newspaper websites, but *how* they use the search engines is different. People who visit well-known newspaper websites are usually referred by search engines after they search for keywords contained in the news articles. People who visit smaller newspapers also use search engines, but they search for the names of specific newspapers or sites rather than using keywords from the articles.

FIGURE 1.5: The share of *direct traffic* out of total online traffic vs. the rank in terms of online traffic

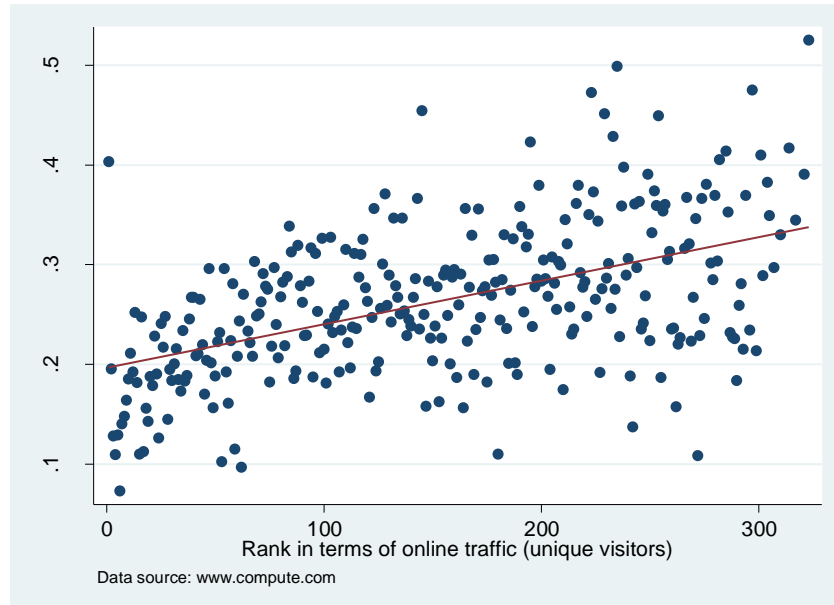
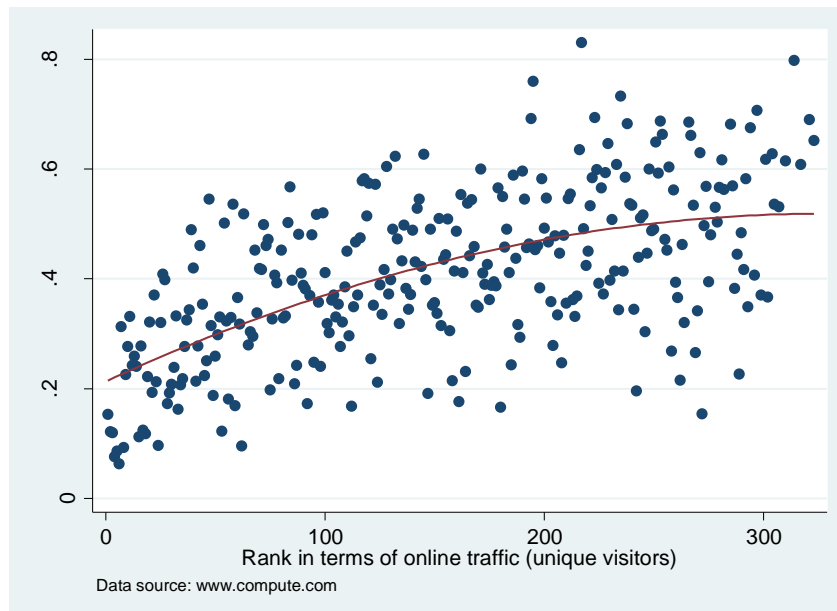


FIGURE 1.6: The ratio of *name search* to the rank in terms of online traffic



1.4.3. DO THE SAME NEWSPAPER COMPANIES CONSISTENTLY BENEFIT FROM THE INTERNET?

As a way to check the robustness of the finding, I test whether the observed benefit that the top news organizations receive is consistent over time. If the observed high concentration results from the inherently volatile nature of online traffic and the same newspapers do not get consistent benefits over time, the findings of this study would be of less concern.

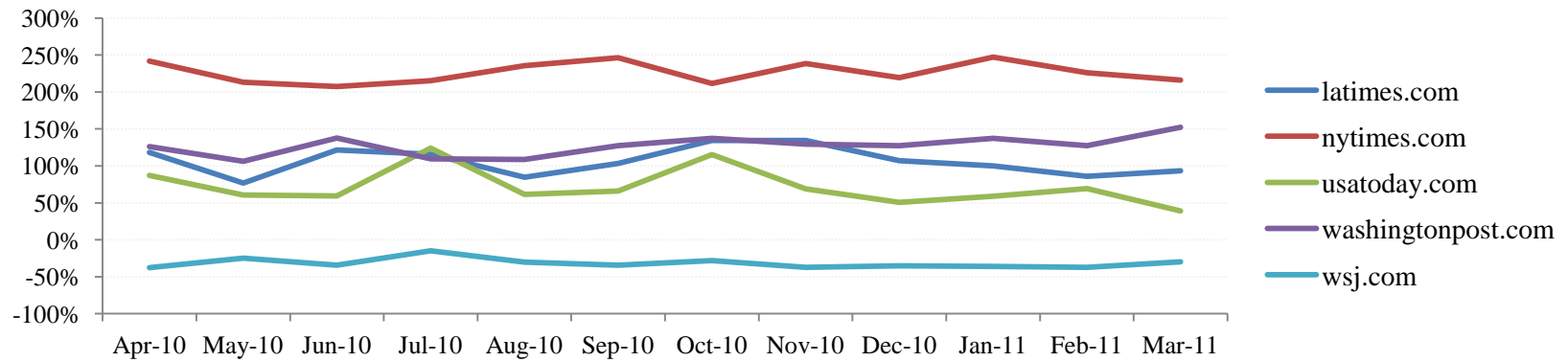
In order to rule out this concern, I calculated the ratio of online readerships to offline readerships for the five biggest news organizations, as follows, and plotted their variations over time. As shown in Figure 1.7, I find that the ratio has been consistent over time for the five biggest news organizations.

$$Ratio = \frac{Online\ readership\ (Unique\ Visitors)_{it}}{Offline\ readership\ (Circulation)_{it}} - 1$$

Table 1.3: Average differences in the offline and online readerships of the five biggest newspaper: April, 2010 - March, 2011

Newspapers	Offline readership (Share of circulation)	Online readership (Share of unique visitors)	The ratio of online readership to offline readership
LA Times	2.16%	4.46%	106%
New York Times	3.21%	10.47%	226%
USA Today	6.55%	11.28%	72%
Washington Post	1.96%	4.46%	127%
Wall Street Journal	7.48%	5.12%	-32%

FIGURE 1.7 : Five largest newspaper companies: offline vs. online readerships



Vertical axis is the ratio of online readership (constructed by unique visitors) to offline readership.

1.5. FINDINGS, DISCUSSION & CONCLUSION

This study finds that news readership is more concentrated and polarized online than offline. The evidence suggests that a very small number of “top” news organizations is driving the high concentration of online news readership. In particular, the online readership of the top 1 percent of news organizations is 39 percent higher than for a comparable group of news outlets offline. I show that the online readership of the five largest newspapers is double their offline readership and that these figures were consistent over the data collection period. The benefit these large organizations receive online seems to surpass considerably the advantages of the physical distribution channels they enjoyed in the offline market. Findings also suggest that news organizations having a group of readers with politically extreme positions command more attention online than offline. *Ceteris paribus*, news sites with the most politically extreme positions generate online traffic that is 8 percent higher than the traffic for those with an average extreme index.

The evidence also suggests that online gatekeepers play a significant role in making online information readerships more concentrated and polarized. I observed both dominance by the largest news organizations and an increase in online readership for politically extreme news outlets, but only when I used online traffic referred by an online gatekeeper to measure online readerships as opposed to when I used *direct traffic*. Because *direct traffic* can be viewed as a proxy for the choices people make when

following their private signals, these findings are better explained by the cascade hypothesis than by the quality hypothesis.

Online gatekeepers make online information vertically less and horizontally more diverse, based on my definition of information diversity. A lower vertical diversity (a higher concentration) may undermine our hope that the Internet will disrupt the long-standing patterns of participatory inequality in American politics by increasing attention to perspectives outside of the mainstream. Further, evidence of the cascade hypothesis indicates that it is incorrect to assume that elite domination—a situation in which “elites induce citizens to hold opinions that they would not hold if aware of the best available information and analysis” (Zaller, 1992, 313)—would necessarily become less prevalent with the Internet.

However, the political implications of higher horizontal diversity (polarization) might be multi-faceted. The increasing polarization of American politics (Poole & Rosenthal 2001) may have potentially negative consequences on democracy. However, in fact, many historical movements that later turned out to be of great value—for instance, civil rights, gender equality, and the antislavery movements—may well have been sparked from voices that were viewed as politically extreme at that time (Sunstein 2007). Similarly, as the recent “Twitter revolution” and the uprisings of the “Arab Spring” suggest, a certain form of online gatekeeping may amplify the voices suppressed by the regime and empower social movements (Diamond 2010, Boyd 2012), but this technology may also be used by criminals and political or religious extremists to maximize their voices (Deibert & Rohozinski 2010).

Two points deserve mention before I conclude. First, this study has been limited to the demand side of online information, but the results imply that online information will be even more polarized if we take into account the behavioral responses on the supply side of information. That is, given the evidence that news sites receive greater online attention by gatekeepers if they provide ideologically extreme news content (Table 1.1), it is possible and even likely that rational news organizations may become increasingly extreme in their editorial positions. More importantly, this evidence suggests that news organizations may become increasingly extreme not only in response to the American audience who increasingly polarizes over matters of politics (Gentzkow & Shapiro 2006) but also in response to people's increasing dependence on online gatekeepers. This important implication should be tested in future research.

Second, previous studies that have examined the Internet's role in the increasing political polarization have looked at *individual* information consumption, rather than consumption in the market as a whole (Negroponte 1995; Sunstein 2002, 2007; Mutz 2006). I agree that *individual* information consumption patterns—if combined with more aggregate-level evidence, such as the type this study presents—may significantly improve our understanding of the Internet's political implications. This important piece of information lies beyond the scope of this study.

Coming back to the question at the beginning of this paper, I argue that the evidence presented in this study shows that online gatekeepers produce a trade-off between the lower costs of access to political information viewed from *individuals'* standpoints, and the higher costs of a more concentrated and polarized online information readership from

the viewpoint of a *market* or *society* as a whole. The costs of online gatekeepers to a society arise not from the mere fact that information becomes more concentrated and polarized, but rather from the underlying mechanisms through which concentration and polarization occur—the cascade hypothesis. This cascading process implies that the risk of elite domination as well as the trade-off between the two central components of deliberative democracy (Fishkin 2009)—*inclusion* and *thoughtfulness*²¹—may persist in many Internet-mediated forms of deliberation. Taken as a whole, this evidence challenges the notion that a greater variety of political information available on the Internet will necessarily benefit democracy.

²¹ For instance, many scholars have argued that democratic reforms that emphasize *inclusion* by providing power to the people tend to undermine collective *thoughtfulness* by failing to motivate citizens to thoroughly consider underlying issues.

1.6. APPENDIX

DATA SOURCES

<i>Variables</i>	<i>Data Source</i>
Circulation	Audit Bureau of Circulation, e-Circ dataset www.accessabc.com
Unique visitors	
Direct traffic	
Search engines traffic	www.compete.com
News aggregators traffic	
Social media traffic	
Extreme index	2008 National Annenberg Election Surveys (NAES)

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CHAPTER 2:

WHY SHOULD WE EXPECT THE CASCADE TO INCREASE OVER TIME?

2.1. INTRODUCTION

According to conventional wisdom, an increase in the number of Internet users will surmount the digital divide and lead to better democracy (e.g., Norris 2001). However, in this chapter, and perhaps counter-intuitively, I show that the increasing number of Internet users leads to a trade-off as long as people rely on online institutions to source information. In other words, an increase in the number of Internet users suggests a more concentrated consumption pattern of online information, since all else being equal, the magnitude of the cascade will increase with the number of Internet users.

In Chapter 1, I showed that the Internet has a negative impact on the diversity of information consumption, due to cascades created by online institutions. In the current chapter, I show that the magnitude of this negative impact may itself increase as the number of Internet users increases. Using a formal analytic model, this chapter explains why an increase in the number of Internet users makes the Internet less, rather than more, diverse, and then tests the prediction by showing evidence of an association between the number of visitors to a news aggregator site and the estimated level of the cascade on the aggregator site.

Many online institutions might create cascades. However, this paper focuses on

online news aggregators. The Internet has reshaped the news industries by providing people with easy access to news. One of the advances of digitization, in turn, has been the development of online aggregators such as Yahoo! News and Google News, which have become major outlets for online news consumption. Indeed, 2010 report by the Pew Project for Excellence in Journalism found that the total amount of traffic to the top three newspaper sites—The New York Times, Washington Post, and USA Today—is less than the traffic to Yahoo! News, the top news aggregator site.

A growing literature explores the role of aggregators and their effects on the economy. Recently, several studies have attempted to incorporate the interplay between website aggregators and readers' consumption of news content. Athey et al. (2011) provide a model that analyzes the impacts of blogs, aggregators, and paywalls on outlet profits from advertising. George and Hogendorn (2012) put forth a model showing how search technology and aggregation can alter both market participation and the number of sites visited which can affect equilibrium prices and profits in the advertising market. Dellarocas et al. (2011) model the implications of interrelated and strategic hyper-linking and content investments.

Although previous models have provided valuable insights into the interplay between website aggregators and content providers, they do not incorporate one of the important roles of aggregators: That is, aggregators *rank* news content, and this ranking is subject to cascade. For example, consider the “most popular” section in Yahoo! News. Because Yahoo! News sorts articles by popularity, any visitor is necessarily affected by the

choices, preferences, and opinions of others.¹ In this case, if people have imperfect information regarding the quality of news content and are therefore more likely to click on content with higher rankings, the result is a cascade.

Several studies have already found evidence of cascades on the Internet, although not with respect to online news aggregators. For instance, Hindman (2008) finds that among the hundreds of thousands of political blogs in the United States, most of the online traffic goes to a handful of mainstream, professionally written blogs. Further, Duan et al. (2008) argue that vast amounts of increasingly sophisticated information, coupled with the availability of information about product popularity and other online users' choices, make cascades more feasible on the Internet. In an experiment, Salganik et al. (2006) find that the availability of information on the choices of others influences both inequality and unpredictability in cultural markets.²

However, an important observation that is missing from previous studies is that cascades will increase with an increase in the number of people visiting aggregator sites. None of the previous studies has provided a model or empirical evidence that incorporates this hypothesis. This is an important omission as it suggests that the level of cascades will be even more important in the future when there is an increase in population using the Internet and the likely dependence of this population on aggregators.

¹ This is also true for other types of aggregators. A similar example can be seen in the case of YouTube, which highlights its most popular videos: this is presented under the tab “most viewed” on the website.

² In addition, in the context of lab experiments (Anderson and Holt, 1997; Celen and Kariv, 2004) or field studies (Cai, Chen and Fang, 2009; Zhang, 2010; Chen, Wang and Xie, 2011), there are several other empirical evidences in favor of “winner-takes-all” conclusions; in other words, popularity information benefits high-volume products.

The present paper provides a simple model that explains how website aggregators affect the online traffic of content providers. Although the model is highly simplified, it provides deep insight into the manner in which the number of people using aggregators, and people's behaviors affect online traffic.³ Section 2 describes the model, Section 3 discusses its welfare implications, and Section 4 presents empirical evidence. Finally, the conclusions are presented in Section 5.

2.2. THE MODEL

2.2.1. EQUILIBRIUM

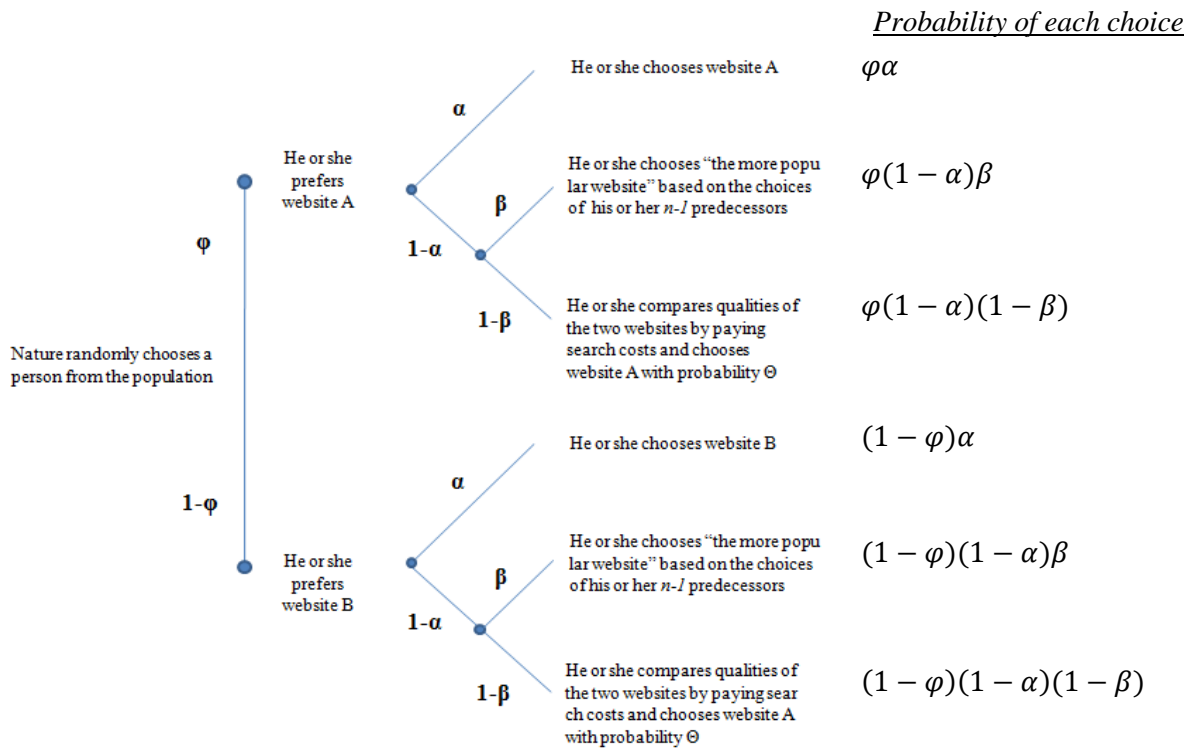
In this section, I describe my model to explain the manner in which people decide which of two news sites to view in an aggregator in which people can see the popularity rank of the news sites. The model can be extrapolated to a more general situation in which people choose to visit a website or click on certain content in an aggregator. Let us suppose that there are two news websites—A and B—that provide news stories on the same topic and therefore directly compete with each other.⁴ In other words, websites A

³ It is important to note that the “aggregators” examined in this study differ from what are known as “user reviews,”³ which allow viewers to provide explicit user feedback or recommendations. I categorize the online reputation systems into two groups of people: those that provide explicit user feedback or recommendations and those that do not. Amazon's “average customer review” and Yahoo! News' “most recommended” sections are examples of user reviews, whereas Yahoo! News' “most popular” section is an example of the latter group, which is the subject of this study. User reviews can moderate the impact of cascades (Duan et al., 2008) as they may provide more accurate information. The purpose of the current model is not to identify the relative importance of these two effects or to separate them.

⁴ Websites A and B are of the same design, which means that they belong to the same category of product or service, and people search by this category when they use an aggregator.

and B fall under the same category within which popularity information is ranked. In this paper, following Bar-Isaac et al. (2011), I define “design” as a category within which popularity information is ranked. Further, suppose that website A is a “first mover” and therefore better known to the public than website B. The decision process of a visitor to the aggregator is depicted in the form of a decision tree in Figure 2.1.

FIGURE 2.1



Suppose there is a population of size N who is interested in visiting either website A or website B, and initially, a proportion φ of the population prefers website A, but the

remainder prefers website B. This situation is represented by $\frac{1}{2} < \varphi < 1$, which is reflective of the fact that website A enjoys the first mover advantage⁵.

The model assumes that people do not have information about the cost quality of the websites, and they can visit aggregators to view the relative popularity of the two websites. Then, one user is selected at random from the entire population N , and he or she makes a decision as follows.⁶ With probability α , the individual merely selects the article from the website he or she used to visit, but with probability $(1 - \alpha)$, the individual searches for information to ascertain which website is better in terms of quality. Further, suppose there is an aggregator on the Internet that provides information on the relative popularity of the two websites. $(1 - \alpha)\beta$ is the probability that the individual visits website A and chooses the website ranked as “the more popular website.” As mentioned earlier, probability $(1 - \alpha)(1 - \beta)$ represents the individual’s search for perfect information on the quality of the two websites, by paying search costs, and his or her choice of the website that has the higher utility, with the probability of choosing website A equal to Θ . Therefore, Θ can be regarded as the relative quality measure of website A to website B, under the assumption that people prefer a website with higher quality. Thus, $\Theta > \frac{1}{2}$ implies that more than half the population prefers website A, the first mover, over website B; website A also has a quality advantage. On the other hand,

⁵ In some studies (e.g. Haugtvedt and Wegener 1994, Xiao and Benbasat 2011), this *first mover advantage* is called a *primary effect*, which refers to a scenario in which the first content posted gets the most attention simply because they are observed first in the list.

⁶ To maintain the simplicity and tractability of the model, I do not explicitly model the consumers’ optimization problem. Instead, I model consumers’ choices with probabilities α and β which, in turn, can be expressed as functions of relevant utility parameters.

$\Theta < \frac{1}{2}$ means that more than half the population prefers website B, the second mover.

$\Theta = \frac{1}{2}$ is a special case where 50 percents of the population prefers A, and the remaining 50 percents prefers B; in this case, neither website has an advantage. Further, assume that consumers' utility functions are such that Θ is continuous between 0 and 1.⁷ More specifically, let q_j be the quality of website $j \in \{A, B\}$ and u_i be the utility of person i .

Then, the relative quality parameter Θ is defined as follows:

$$\Theta = \Pr[u_i(q_A) > u_i(q_B)] = f\left(\frac{q_A}{q_B}\right)$$

where $f\left(\frac{q_A}{q_B}\right)$ is an increasing function of $\frac{q_A}{q_B}$. Here, I define quality as the subjective value of the news information, which might be “either personally useful or merely entertaining” (Zaller, 2003), and thus do not assume that soft news is necessarily inaccurate or inferior (Baum, 2003, 2005; Baum and Jamison, 2006).

Note that the website selected as the more popular website is not necessarily the one with the higher quality, as popularity does not automatically imply quality. In this model, I assume that the cost of visiting aggregators and the cost involved in choosing the more popular website are lower than the cost of searching for accurate quality information on both websites; I also assume that some people will trade accuracy of information for lower cost ($0 < \beta < 1$). Explicit feedback or recommendations provides potential customers with quality information on products; therefore, probability $(1 - \alpha)\beta$ in the

⁷ People may have different preferences for the same product.

model is related to people's visits to aggregators without explicit feedback or recommendations.

The decision of the model is sequential. Let ω_n represent the event in which website A is selected as the more popular one at the time when the n th person makes his or her decision; let $\mathbb{E}(\omega_n)$ represent the expected probability of this event. Further, let us suppose that once exposed to a website never previously visited, a person may highly appreciate its quality. Let us assume that the preference for one website over another can be affected by a person's experience with either website; there is a chance, ξ , that people can change their preferences when they visit a website they do not like. Then, as seen in Figure 1, the expected probabilities of the randomly chosen n th person choosing website A or B are as follows:

$$P_n(A) = \alpha \mathbb{E}(\varphi_{n-1}) + (1 - \alpha)\beta \mathbb{E}(\omega_{n-1}) + (1 - \alpha)(1 - \beta)\theta \quad (1)$$

$$P_n(B) = \alpha(1 - \mathbb{E}(\varphi_{n-1})) + (1 - \alpha)\beta(1 - \mathbb{E}(\omega_{n-1})) + (1 - \alpha)(1 - \beta)(1 - \theta) \quad (2)$$

where $\mathbb{E}(\varphi_{n-1})$ is the proportion of "website A lovers" when $n > 1$. Because website A initially has the first mover advantage, I assume that $\frac{1}{2} < \varphi_0 < 1$ and $\mathbb{E}(\omega_0) = \varphi_0$. Therefore, after the n th individual makes his or her choice, the proportion of website A lovers is as follows:

$$\begin{aligned}
\mathbb{E}(\varphi_n) &= \mathbb{E}(\varphi_{n-1}) - \Pr_n(A \rightarrow B) + \Pr_n(B \rightarrow A) \\
&= \mathbb{E}(\varphi_{n-1}) - \underbrace{(1 - \alpha)\xi\{\mathbb{E}(\varphi_{n-1}) - \Theta - \beta\{\mathbb{E}(\omega_{n-1}) - \Theta\}\}}_{0 \text{ in equilibrium}} \quad (3)
\end{aligned}$$

where $\Pr_n(A \rightarrow B)$ is the probability that the n th player is a website A lover who switches to website B; $\Pr_n(B \rightarrow A)$ represents the reverse probability. In this paper, *equilibrium* is defined as the state at which the system of equations and, therefore, all variables of interest— $\mathbb{E}(\varphi_n)$, $P_n(A)$, and $\mathbb{E}(\omega_{n-1})$ —do not change in n . Because $\mathbb{E}(\varphi_n) = \mathbb{E}(\varphi_{n-1})$ must hold in equilibrium, I am able to ascertain the equilibrium proportion of website A lovers, $\mathbb{E}(\varphi_n)$, as well as the equilibrium probability of a person choosing website A, $P_n(A)$:

$$P_n(A) = \mathbb{E}(\varphi_n) = \Theta + \beta \left\{ \lim_{n \rightarrow k} \mathbb{E}(\omega_{n-1}) - \Theta \right\} \quad (4)$$

where $\lim_{n \rightarrow k} \mathbb{E}(\omega_{n-1})$ denotes the value of $\mathbb{E}(\omega_{n-1})$ in equilibrium, and k is the value of n in equilibrium. From the equilibrium condition in Equation (4),⁸ we see that equilibrium $\mathbb{E}(\varphi_n)$ and $P_n(A)$ depend on the value of $\lim_{n \rightarrow k} \mathbb{E}(\omega_{n-1})$, which can be either 1 or 0 when

⁸ The meaning of the number n will depend on how often the aggregator updates its ranking. For example, if Yahoo! News provides a weekly “most viewed news” ranking, then parameter n will refer to the number of clicks or unique visitors generated within the span of one week.

$\varphi_0 > \frac{1}{2}$ holds. This is explained in Appendix B. Let $\tilde{\Theta}$ be the “cutoff” quality parameter, which is defined as follows:

DEFINITION 1: The cutoff quality parameter $\tilde{\Theta}$ represents the value of quality parameter Θ , which satisfies the following property:

$$\lim_{n \rightarrow k} \mathbb{E}(\omega_{n-1}) = \begin{cases} 1, & \Theta \geq \tilde{\Theta} \\ 0, & \Theta < \tilde{\Theta} \end{cases}$$

where $0 < \tilde{\Theta} < \frac{1}{2}$ holds.

I then obtain the following proposition.

PROPOSITION 1: The equilibrium proportion of website A lovers, $\mathbb{E}(\varphi_n)$, and the equilibrium probability that a person will choose website A, $P_n(A)$, are as follows:

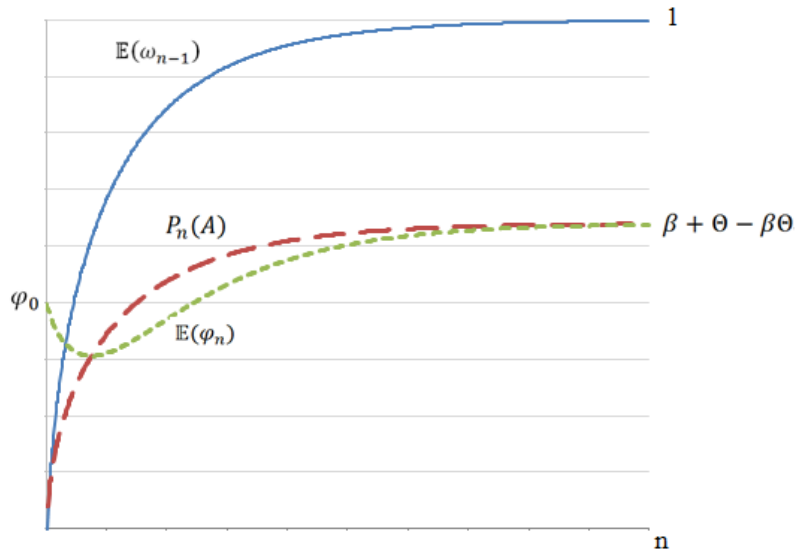
$$P_n(A) = \mathbb{E}(\varphi_n) = \underbrace{\Theta}_{\text{Quality}} + \beta \underbrace{\left\{ \lim_{n \rightarrow k} \mathbb{E}(\omega_{n-1}) - \Theta \right\}}_{\text{Cascade}} \quad (5)$$

Equilibrium $\mathbb{E}(\varphi_n)$ and $P_n(A)$ has two components. In other words, people choose website A over website B for either of two reasons: website A is relatively better than

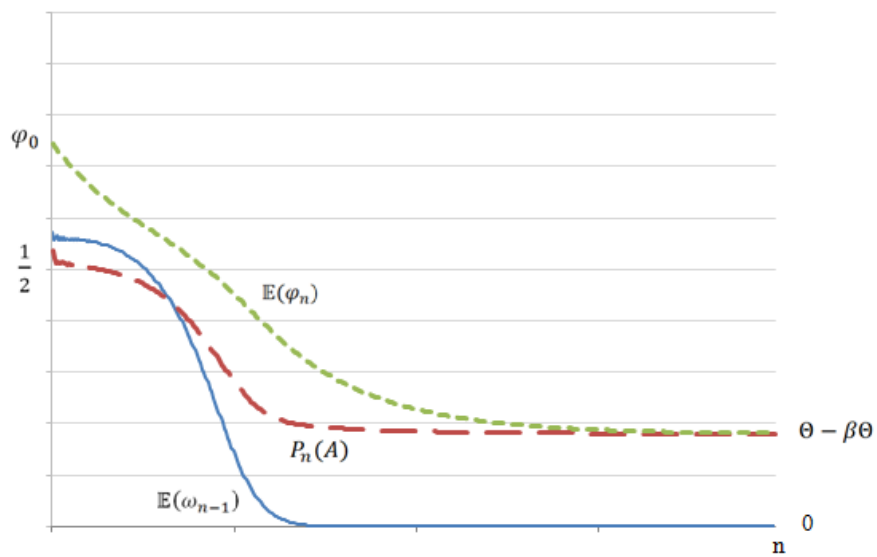
website B in terms of quality (“quality”), or website A is selected as the more popular site by the aggregator (“cascade”).

FIGURE 2.2: Equilibrium $\mathbb{E}(\varphi_n)$, $P_n(A)$, and $\mathbb{E}(\omega_n)$

I. $\theta \geq \tilde{\theta}$



II. $\theta < \tilde{\theta}$



Combining Equation 5 with Definition 1 yields the following equation:

$$P_n(A) = \mathbb{E}(\varphi_n) = \begin{cases} \beta + \Theta - \beta\Theta, & \Theta \geq \tilde{\Theta} \\ \Theta - \beta\Theta, & \Theta < \tilde{\Theta} \end{cases}$$

2.2.2 COMPARATIVE STATIC

Since equilibrium $P_n(A)$ and $\mathbb{E}(\varphi_n)$ depend on whether Θ is greater or less than the cutoff, $\tilde{\Theta}$, the model implication is greatly affected by $\tilde{\Theta}$. Proposition 2 shows how cutoff $\tilde{\Theta}$ is affected by various model parameters.

PROPOSITION 2: The cutoff, $\tilde{\Theta}$, decreases, and therefore, the probability of there being a positive first mover advantage increases

(\mathcal{A}) as consumer brand loyalty increases (i.e., an increase in α).

(\mathcal{B}) as consumers rely more on aggregators (i.e., an increase in β).

(\mathcal{C}) in the initial share of consumers who prefer the first mover (i.e., an increase in φ_0).

PROOF: See Appendix A.

2.2.3. CASCADING EFFECT

It is often believed that if a product is of higher quality, this product will benefit from the Internet because with lower switching costs (Porter, 2001; Athey et al, 2011), the

consumer will naturally gravitate toward the higher-quality choice. However, in the case of aggregators, there is no guarantee that the one with the quality advantage will benefit from the Internet. People will try to save search costs by using aggregators, but this saving comes at the expense of less accurate information on quality. In this chapter, I define “cascade” as the difference between what consumers actually chose and what they would have chosen if they had perfect information on quality. Then, I show how cascade on the Internet increases with an increase in the number of visitors to aggregators. It is also important to note that cascade will be maximized in an absolute value if the qualities of competing products are similar. Intuitively, when there is a large difference in quality, most people will choose the option with higher quality, and aggregators will also pick the higher quality one as the more popular choice. However, if there is a minimal quality difference, consumers’ preferences will be divided almost equally for the two products, and aggregators will be likely to rank the two products and pick only one; however, this could mean that the selected product could be the one with the slightly lower quality if it was the first mover.

For a formal representation of these implications, let me define the cascading effect, \mathbb{C}_n .

DEFINITION 2: Cascading effect \mathbb{C}_n is defined as follows:

$$\mathbb{C}_n = P_n(A) - \Theta$$

In the absence of aggregators, people would have chosen website A with probability Θ in equilibrium. Thus, *cascading effect* \mathbb{C}_n is the difference between the equilibrium probability of a person choosing website A and the relative quality of website A. Therefore, \mathbb{C}_n represents the magnitude of cascades on the Internet.

PROPOSITION 2: The magnitude of cascade \mathbb{C}_n

(A) increases in absolute value as the number of Internet users, n , increases.

(B) is positive if $\Theta \geq \tilde{\Theta}$, and negative if $\Theta < \tilde{\Theta}$.

(C) is always positive if $\Theta = \frac{1}{2}$ (if neither A nor B has a quality advantage, then the first mover will benefit from aggregators).

(D) is maximized when Θ is just above cutoff $\tilde{\Theta}$, and minimized when Θ is just below cutoff $\tilde{\Theta}$.

(E) is a function of the relative quality advantage of the first mover Θ and people's behavior β (i.e., the tendency to use an aggregator).

PROOF: See Appendix A.

2.3. WELFARE IMPLICATION

In this section, I examine the welfare implication of using an aggregator. In order to keep the model as simple as possible while maintaining key implications, I assume $\xi = 1$. Let us suppose that the population can be divided into two types: types a and b . Type a represents people who prefer website A over B, and type b represents those who prefer website B over A. From the entire population, the proportion of type a is Θ , and that of type b is $1 - \Theta$. Since people do not have perfect information about quality, the type a and type b population can represent those who prefer website B and website A, respectively. The decision of the model is sequential, and the n th player is randomly chosen from the population. Then, in equilibrium, the following lemma must hold.

LEMMA 2: Let P_n^i and $\mathbb{E}(\varphi_n^i)$ be $P_n(A)$ and $\mathbb{E}(\varphi_n)$, respectively, for each type $i \in \{a, b\}$. Then, in equilibrium, we have the following:

$$P_n^a = \mathbb{E}(\varphi_n^a) = \beta \mathbb{E}(\omega_{n-1}) + 1 - \beta$$

$$P_n^b = \mathbb{E}(\varphi_n^b) = \beta \mathbb{E}(\omega_{n-1})$$

PROOF: See Appendix A.


Let u_A^i and u_B^i be the utilities of consuming websites A and B, respectively, for each type $i \in \{a, b\}$, where $u_A^a > u_B^a$ and $u_A^b < u_B^b$ hold by definition. A person pays a search cost

of c_1 when using an aggregator, and a search cost of c_2 when searching for perfect information on the two websites. The expected search cost for any player is $c = (1 - \alpha)\beta c_1 + (1 - \alpha)(1 - \beta)c_2$. Thus, assuming $c_1 < c_2$ (i.e., using an aggregator saves search cost), the expected utility becomes a linear equation in β as follows:


$$\mathbb{E}(\mathcal{W}_n) = u_0 + \left\{ \begin{array}{l} \Theta(1 - \mathbb{E}(\omega_{n-1}))(u_B^a - u_A^a) + (1 - \Theta)\mathbb{E}(\omega_{n-1})(u_A^b - u_B^b) \\ + (1 - \alpha)(c_2 - c_1) \end{array} \right\} \beta$$

where $u_0 = \Theta u_A^a + (1 - \Theta)u_B^b - (1 - \alpha)c_2$ is the equilibrium expected utility in the absence of aggregators. Thus, the marginal benefit of using an aggregator is as follows:

$$\frac{\partial \mathbb{E}(\mathcal{W}_n)}{\partial \beta} = \left\{ \begin{array}{ll} (1 - \Theta)(u_A^b - u_B^b) & + \quad (1 - \alpha)(c_2 - c_1), & 1 \geq \Theta \geq \tilde{\Theta} \\ \Theta(u_B^a - u_A^a) & + \quad (1 - \alpha)(c_2 - c_1), & 0 \leq \Theta < \tilde{\Theta} \end{array} \right.$$



Imperfect information



Search cost reduction

The marginal utility of using an aggregator, $\frac{\partial \mathbb{E}(\mathcal{W}_n)}{\partial \beta}$, can be either positive or negative depending on the relative magnitude of the following two components: (1) imperfect information and (2) search cost reduction. Imperfect information is negative or zero, and search cost reduction is always positive. Therefore, the use of an aggregator necessarily involves a tradeoff in expected utility; although a person can save on search costs by

using an aggregator, the resulting quality of the received information is no better than it would otherwise be with a full information search. This result is further analyzed in Proposition 3.

PROPOSITION 3 The use of an *aggregator* necessarily involves a tradeoff in expected utility; search cost saving comes at the expense of imperfect information. Assuming $u_A^b - u_B^b = u_B^a - u_A^a < 0$, the marginal utility of using an *aggregator* is minimized when $\Theta = \tilde{\Theta} + \varepsilon^9$ and maximized when Θ is either 1 or 0, when ε is a sufficiently small number.

PROOF: See Appendix A.

Proposition 3 has an important implication because it suggests that the use of an aggregator may not always be welfare enhancing. For example, if either $u_A^b - u_B^b$ or $u_B^a - u_A^a$ is sufficiently large in its absolute value, the disutility from imperfect information may be greater than the utility from search cost saving. In this case, the marginal utility of using an aggregator may become negative.

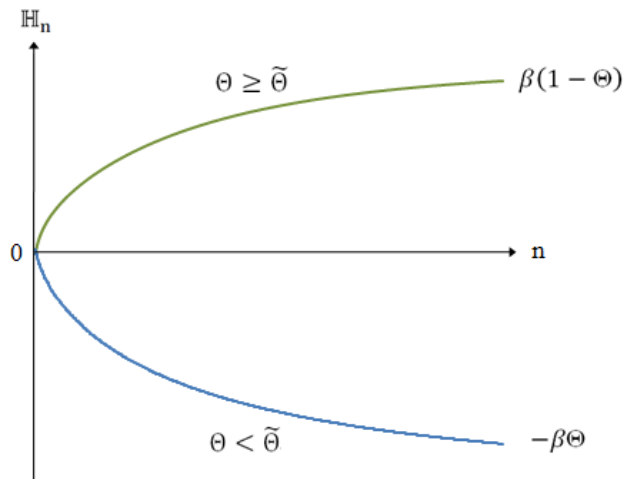
Proposition 3 also suggests that the social welfare implications of aggregators greatly depend on the relative quality of the competing products. This result suggests that aggregators are more likely to be welfare enhancing in a market in which people have similar opinions about the quality of competing products, (i.e., Θ is either 0 or 1);

⁹ The value of $\frac{\partial E(W_n)}{\partial \beta}$ at $\Theta = \tilde{\Theta} - \varepsilon$ is greater than that at $\Theta = \tilde{\Theta} + \varepsilon$.

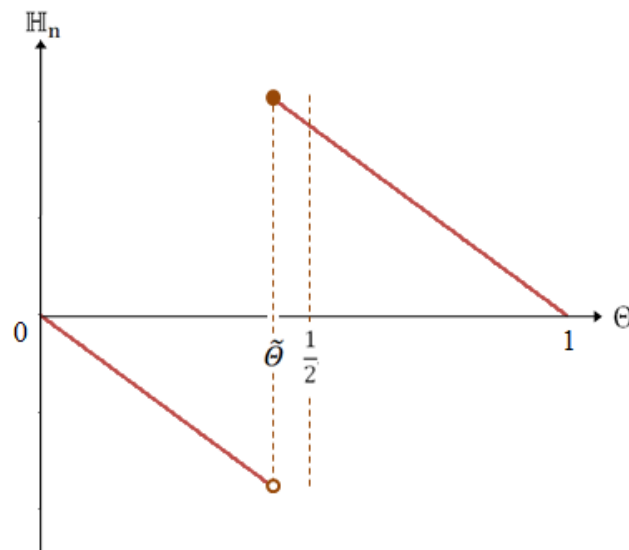
contrarily, aggregators are less likely to be welfare enhancing when people have heterogeneous tastes.

FIGURE 2.3: Graphical illustration of Proposition 3

I. Number of Internet Users vs. Cascading effect



II. First Mover's Relative Quality Advantage vs. Cascading effect



Proposition 3 also provides insight into the manner in which aggregators should set the scope of their popularity information in order to minimize their social costs. Social costs resulting from imperfect information are minimized when the range of products that are under the same umbrella of popularity ranking is as narrow as possible. If aggregators provide a popularity ranking by comparing somewhat heterogeneous products, then people are more likely to have heterogeneous tastes over the competing products (i.e., Θ is less likely to be either 0 or 1). In this case, the ranking provided by aggregators cannot mislead a significant number of people.

2.4. EMPIRICAL EVIDENCE

In the model, the key variable that drives the cascading effect is $\mathbb{E}(\omega_{n-1})$, the probability that the first mover will be selected as *the most popular website*. Thus, instead of looking at the magnitude of cascade, I propose an empirical test of $\mathbb{E}(\omega_{n-1})$. The key feature of $\mathbb{E}(\omega_{n-1})$ is that it increases with the number of Internet users, n , when $\Theta \geq \tilde{\Theta}$ holds, and decreases with n when $\Theta < \tilde{\Theta}$ holds. But as Θ and $\tilde{\Theta}$ are not directly observable, it is not straightforward to implement an empirical test. Furthermore, having more than two competing websites in a market makes an empirical test of the model even more challenging. However, if I restrict our attention to a market where the first mover enjoys the highest market share, it is reasonable to believe that $\Theta \geq \tilde{\Theta}$ should hold in this market (i.e., the quality of information from news organization that enjoys the greatest market share is at least as good as the quality of other news information.). Therefore, in

this market, *ceteris paribus*, the probability that the first mover will be selected as *the most popular website* should increase with the number of visitors to the site providing the ranking.

In this section, I present an empirical test of the key features of $E(\omega_{n-1})$, using online news traffic data from Naver, a South Korean web portal, which is the world's fifth¹⁰ largest search service provider, behind Google, Yahoo, Baidu and Microsoft, and has dominated the Korean search market¹¹. There are two reasons I rely on Naver as the data source. The most important reason is that Naver has publicly maintained in its website¹² a historical dataset of "the most popular news stories" since mid-2000s. This public dataset is valuable, as other international major information aggregators such as Yahoo!, Google, and AOL have not publicly released or maintained a historical dataset of its kind. Second, Korea is one of the five countries in the world that had the highest broadband penetration as of June 2007 (OECD 2008). This gives us a large variation in our independent variable and a more credible estimate of the effect of interest.

Thus my empirical strategy aims to verify that the probability that the first mover will be selected as the most popular website, and thus the magnitude of cascade, increase as the number of visitors to the aggregator site increases. (i.e. $\frac{\partial E(\omega_n)}{\partial n} > 0$ holds if $\Theta \geq \tilde{\Theta}$ holds). Thus, the empirical specification is:

¹⁰ The Associated Press, 9 Oct 2007

¹¹ As of December 2010, www.naver.com is ranked 53rd in "the 1000 most-visited sites on the web (worldwide)" by Google. (See <http://www.google.com/adplanner/static/top1000>).

¹² <http://news.naver.com/main/ranking/popularWeek.nhn>.

$$TOPNEWS_{it} = \rho_0 + \rho_1 UV_t + \theta QUAL_t + f(t) + \phi_i + \varepsilon_{it} \quad (9)$$

where $TOPNEWS_{it}$ is the weekly probability that the first mover will be selected as *the most popular news* in section i , at time t , which I use as a proxy for $\mathbb{E}(\omega_n)$ in the model. Naver selects 30 news stories each week as *the most popular news* in each section i , and thus $TOPNEWS_{it}$ is the total number of news stories supplied by the first mover selected as *the most popular news* at time t out of the top 30. UV_t is the weekly number of unique visitors to the Naver website. $QUAL_t$ is a proxy for the relative quality variable θ in the model, using the weekly number of “direct” traffic¹³ to the first mover relative to the “direct” traffic to all news organizations supplying news stories to Naver combined. “Direct” traffic refers to the online traffic that is not referred by any other websites (e.g., when a person types *www.nytimes.com* directly into the web address bar and visits the *New York Times* website). I use the relative “direct” traffic to the first mover as a proxy for the variable θ in the model as I assume, as in Chapter 1, that *direct traffic* must reveal people’s true preferences based on their private signals concerning the quality. The function $f(t)$ reflects overall time trends in the dependent variable, which I either parameterize using a linear or a quadratic polynomial or rely on nonparametric functional form by including dummy variables. I expect that the coefficient of interest, ρ_1 , is positive as the model indicates that $\frac{\partial \mathbb{E}(\omega_n)}{\partial n} > 0$ holds if $\Theta \geq \tilde{\Theta}$ holds.

¹³ I also use (1) the asset size of the first mover company relative to the asset sizes of all Korean newspaper companies combined, (2) relative number of employees and (3) relative operating profits instead relative “direct” online traffic.” The estimates were all very similar, so I just report the results with the relative “direct” online traffic.

Then how can we identify the first mover? In this case, I consider the Yonhap news agency in Korea to be the first mover. A news agency is an organization of journalists that supplies news reports to newspaper companies and Yonhap is the single news agency in Korea. Yonhap is the first mover because a news agency can set the agenda and release its news faster than other newspaper companies, as many newspaper companies reproduce news provided by the agency. Furthermore, as can be seen in Appendix B, Naver has reserved a separate “breaking news” section only for Yonhap in its main webpage, providing Yonhap with the status of first mover.

FIGURE 2.4: Online Screen Shot of Naver (www.naver.com)



Naver has reserved a separate "breaking news" section only for Yonhap news, which provides Yonhap with a first-mover advantage.

Thus, following a certain event, news from Yonhap tends to show up faster on the Naver website, and therefore is more likely to be selected as *the daily most popular news* relative to news from other news companies. Once it shows up in *the daily most popular news*, it will receive even greater attention and is more likely to be selected as *the weekly most popular news*.¹⁴ This first move advantage will increase in the number of people visiting Naver as Proposition 2 suggests (i.e. coefficient ρ_1 will be positive).

As will be explained in the data section, Naver has categorized its historical data of *the weekly most popular news* by several common themes, which they call “sections”. In total, there are eight sections¹⁵: politics, business, society, culture, science, world, sports, and entertainment. Using data classified into sections has several advantages. First, the number¹⁶ and kind of newspapers providing news articles to Naver differs for each section. This is because there are newspaper companies which specialize in particular areas such as sports, entertainment, business, and world news. Second, people's preferences might be different for news in different sections. For instance, consumers may feel that speed is crucial for news on the business, but they may feel less so for world news. By using data classified into different sections and using the section fixed

¹⁴ This has been confirmed by an interview with a manager of the media relation team at Naver.

¹⁵ For the empirical test, I will restrict our attention to six out of eight sections. These are the sections in which Yonhap, the first mover, has had the highest probability of being selected as *the most popular news* on average, and therefore I believe $\theta \geq \tilde{\theta}$ is a reasonable assumption. The other two sections are sports and entertainment news. In the sports and entertainment sections, Yonhap did not belong to one of the top online news companies. Given the fact that there are a significant number of online news companies specializing in sports and entertainment, I cannot tell with confidence whether $\theta \geq \tilde{\theta}$ or $\theta < \tilde{\theta}$ holds in those sections. This makes it difficult to draw a clear prediction from the model. Therefore, I exclude those two sections from our analysis.

¹⁶ For each section, the list of newspaper companies providing news to Naver has been stable over time except for the sports section. In the sports section, there have been several online news companies specializing in either baseball or soccer, and some of them have provided news only during the seasons of their respective coverage areas.

effect, I can control for these heterogeneities across sections that might otherwise bias our regression estimates.

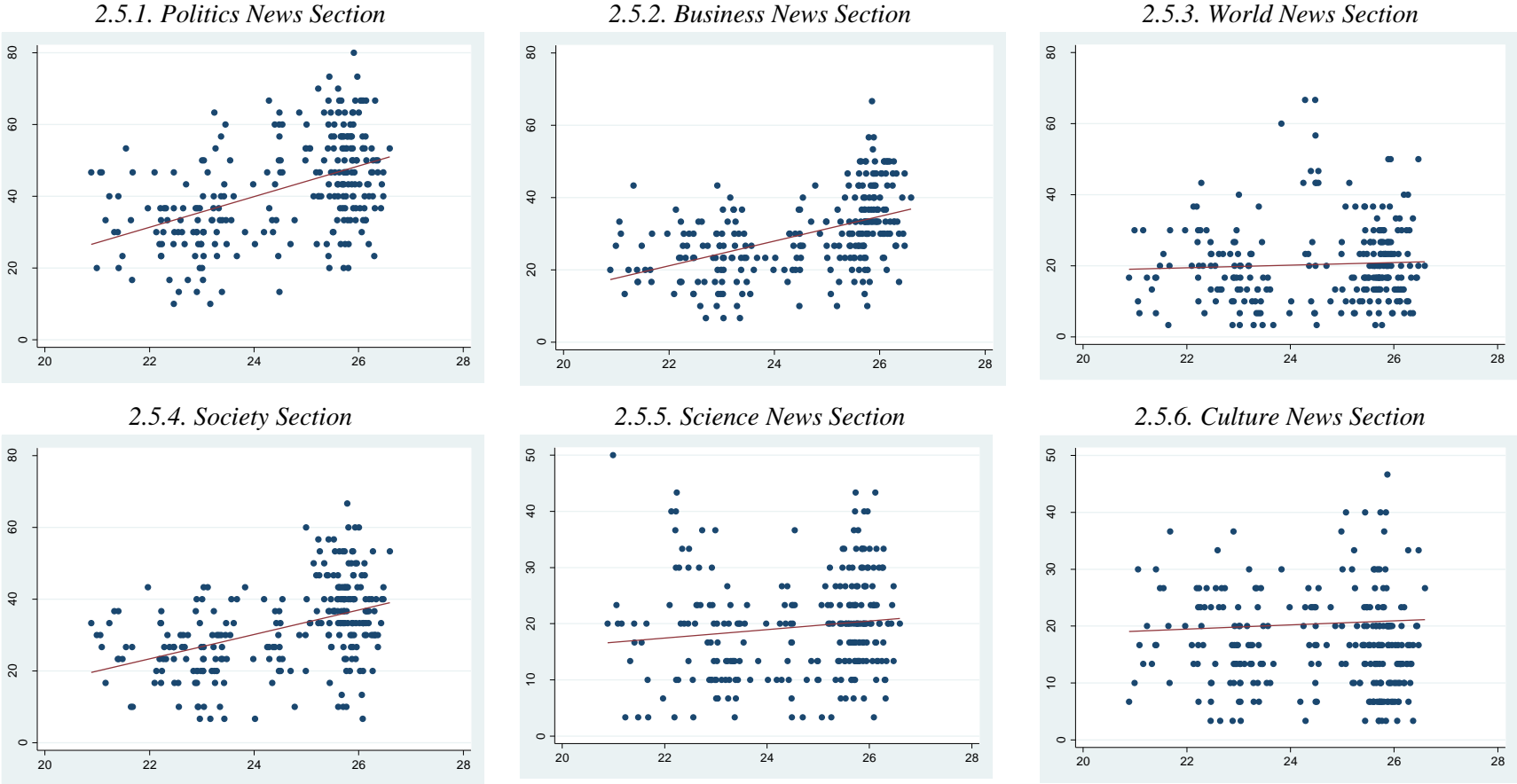
Table 2.1 reports the estimates of Equation (9). Taken altogether, the number of visitors to Naver is positively associated with the probability that news from Yonhap is selected as *the weekly most popular news*; a one standard deviation increase, which is a 1.5 million increase, in the weekly number of visitors to Naver is associated with about a 3.8 percentage point increase in the probability of being selected as “*most popular*”. This positive association is also obvious in Figure 2.5, which show scatter-plots between the two variables in different sections.

TABLE 2.1 : The effect of online traffic on the prob. of the first mover being ranked as a top news in a news aggregator

	Dependent variable: TOPNEWS (%)					
	(1)	(2)	(3)	(4)	(5)	(6)
UV (in millions)	1.973** (0.209)	1.989** (0.172)	1.848** (0.212)	2.479** (0.393)	2.043** (0.590)	2.539** (0.760)
QUAL			1.504* (0.787)	2.070** (0.660)	2.288** (0.686)	1.355 (2.222)
Time				-0.015* (0.009)	0.015 (0.031)	
Time squared					-0.000 (0.000)	
Section fixed effect		√		√	√	√
Linear time trend				√		
Quadratic time trend					√	
Nonparametric time trend						√
Number of Obs.	1,557	1,557	1,557	1,557	1,557	1,557

• Standard errors in parentheses: * p < 0.10, ** p < 0.05

FIGURE 2.5 : Scatter-plots: Online traffic to a news aggregator site vs. Prob. of the first mover being ranked as a top news



Note: 1. The horizontal axis: the number of unique visitors to the Naver website (unit: million).
2. The vertical axis: the probability that news articles supplied by the Yonhap news agency (the first mover) will be selected as the most popular news of the week.

2.5. CONCLUSION & LIMITATIONS

In this study, I have put forth a simple model of aggregators; there are, though, several limitations to this model. One of the aspects not addressed by the model is the entry and exit of suppliers (for example, the entry of new content providers other than websites A and B). Although the entry and exit of suppliers are important phenomena, the implications of the model are not significantly affected by their omission, especially because the model deals with competition *within each design*. The results of the model suggest that cascades tend to benefit the first mover within each design, thereby implying that the existence of aggregators will provide suppliers with the incentive to develop newer designs, becoming the first movers of these. This result is consistent with the findings of Bar-Isaac et al. (2011).

Another aspect that the model did not incorporate is consumers' endogenous decision to use aggregators. In this study, the consumers' decision on whether to stick to their preferences or use the aggregator is randomized with exogenous probabilities α and β . There are two reasons why consumers' decisions are not modeled as endogenous. First, it is not clear whether people visit aggregator sites as a result of rational decision making. Many people may choose to visit Google News or Yahoo! News for behavioral reasons such as inertia, as opposed to rational processes. Second, incorporating consumers' endogenous decisions into the model produces the same implication, but the model becomes less tractable when the number of visitors to aggregator, n , is greater than two.

Although the current model is a highly reduced-form model, it provides better insight into the manner in which equilibrium online traffic reaches an equilibrium state.

Let me outline two future directions for the current study. (1) This paper has put forth a highly simplified model that explains how people's choices of clicks are affected by aggregators. The model can be further developed in a number of ways, such as modeling demand side utility function, expanding the number of suppliers, and incorporating their strategic interactions. (2) The model has important implications and applications that extend beyond the context of this paper. Despite the growing influence of the Internet, relatively few studies have examined how the Internet influences choices among consumers and competition between producers. The framework proposed in this study can be extrapolated to political science, marketing, media economics, and other fields, and can be extended to answer a wide range of questions related to how people adopt new information on the Internet.

Coming back to the political implications of the Internet, the finding of this study implies that, perhaps counter-intuitively, the negative impact of the Internet on the diversity of information consumption may increase as the number of Internet users increases. This is because the magnitude of the cascade in an online gatekeeper such as a news aggregator may increase, *ceteris paribus*, in the number of people visiting the online gatekeeper.

2.6. APPENDIX

APPENDIX 2.A : Proofs

Proof of Proposition 3

(A) From Appendix B, we know that $\mathbb{E}(\omega_{n-1})$ can converge to either 1 or 0. If $\mathbb{E}(\omega_{n-1})$ converges to 1, which means that $\mathbb{E}(\omega_{n-1})$ increases in n , then $P_n(A)$ and therefore \mathbb{C}_n will also increase in n . Similarly, if $\mathbb{E}(\omega_{n-1})$ converges to 0, which means that $\mathbb{E}(\omega_{n-1})$ decreases in n , then $P_n(A)$ and therefore \mathbb{C}_n will also decrease in n . In the latter case, \mathbb{C}_n will decrease and converges to a negative value of $-\beta\Theta$, as shown below. This means that \mathbb{C}_n increases in absolute value in both cases.

(B) From Proposition 3, \mathbb{C}_n takes following values in equilibrium. With $0 < \beta, \Theta < 1$, \mathbb{C}_n is positive if $\Theta \geq \tilde{\Theta}$, and negative if $\Theta < \tilde{\Theta}$. This tells us that if the relative quality level of the first mover is above a certain cutoff, $\tilde{\Theta}$, then the first mover benefits from expansion of the Internet due to aggregators. However, if the quality of the first mover is below the threshold, then the first mover will lose its customers more quickly with the Internet than without it.

$$\mathbb{C}_n = \begin{cases} \beta(1 - \Theta) & \text{if } \Theta \geq \tilde{\Theta} \\ -\beta\Theta & \text{if } \Theta < \tilde{\Theta} \end{cases}$$

(C) This immediately follows from Proposition A2 in Appendix A.

(D) \mathbb{C}_n is maximized when $\Theta = \tilde{\Theta}$ and minimized when $\Theta = \tilde{\Theta} - \varepsilon$ with a small number ε .

(E) This immediately follows from Definition 2 and Proposition 1.

Proof of Lemma 2

In equilibrium, Equation (5) must hold separately for type a and type b , with the parameter Θ in Equation (5) redefined as 1 for type a and as 0 for type b . A simple algebra gives us the lemma.

Proof of Proposition 2

Suppose that $\mathbb{E}(\omega_{n-1})$ stays stable at a number between zero and one for $n \in [u, u + v]$, if $\Theta \approx \tilde{\Theta}$ holds, where u is a sufficiently large integer and v is either an integer or a positive infinity. For $\mathbb{E}(\omega_n)$ to be stable with $n \in [u, u + v]$, we should have $P_u(A) = P_{u+v}(A) = \frac{1}{2}$ (see Appendix B for further details), and Equation (3) becomes the following for $n \in [u, u + v]$:

$$P_n(A) = \frac{1}{2} = \mathbb{p}(\alpha, \beta, \varphi_0, \omega_0, \tilde{\Theta})$$

where $\mathbb{p}(\alpha, \beta, \varphi_0, \omega_0, \tilde{\Theta})$ represents the right hand side of Equation (3). Then assuming \mathbb{p} is a well-behaved function at $\Theta = \tilde{\Theta}$, we may write:

$$\tilde{\Theta} = \mathbb{q}(\alpha, \beta, \varphi_0, \omega_0)$$

where \mathfrak{q} is a function defined so that $\frac{1}{2} \equiv \mathbb{p}(\alpha, \beta, \varphi_0, \omega_0, \mathfrak{q}(\alpha, \beta, \varphi_0, \omega_0))$. By the implicit function theorem, we have:

$$\frac{\partial \tilde{\Theta}}{\partial \alpha} = - \frac{\partial \mathbb{p} / \partial \alpha}{\partial \mathbb{p} / \partial \tilde{\Theta}} < 0 \quad \frac{\partial \tilde{\Theta}}{\partial \beta} = - \frac{\partial \mathbb{p} / \partial \beta}{\partial \mathbb{p} / \partial \tilde{\Theta}} < 0 \quad \frac{\partial \tilde{\Theta}}{\partial \varphi_0} = - \frac{\partial \mathbb{p} / \partial \varphi_0}{\partial \mathbb{p} / \partial \tilde{\Theta}} < 0$$

Proof of Proposition 3

The marginal benefit of using an aggregator is a piece-wise linear function of Θ with a breakpoint at $\Theta = \tilde{\Theta}$. A simple algebra shows that it is maximized when Θ is either 1 or 0, and minimized when $\Theta = \tilde{\Theta} + \varepsilon$.

APPENDIX 2.B : Aggregators

In equilibrium, both $\mathbb{E}(\varphi_n)$, and $P_n(A)$, depends on $\mathbb{E}(\omega_{n-1})$ which drives cascades in the model. The probability that website A will be selected as the most popular news, $\mathbb{E}(\omega_{n-1})$, is the probability that the number of successes is greater than $\frac{1}{2}$ in a Poisson binomial distribution with success probabilities $P_1, P_2, P_3, \dots, P_{n-1}$. Formally, we consider the sum \mathfrak{S}_n of $n \in \mathbb{N} = \{1, 2, \dots\}$ independent Bernoulli random variables X_1, \dots, X_n with success probabilities, $P_1, P_2, P_3, \dots, P_n$. Then, we have

$$\mathbb{E}(\omega_n) = \Pr\left(\mathfrak{S}_n \geq \frac{n}{2}\right)$$

As the distribution $\mathcal{P}^{\mathfrak{S}_n}$ of \mathfrak{S}_n has a complicated structure, it is often approximated by other distributions. In this paper, I approximate¹⁷ $\mathcal{P}^{\mathfrak{S}_n}$ by a binomial distribution $\mathfrak{B}(n, p)$ with number of trials n and success probability $p = \frac{\sum_{i=1}^n P_i}{n}$. Then, $\mathbb{E}(\omega_{n-1})$ is the probability that the number of success from $\mathfrak{B}(n, p)$ is greater than or equal to $\frac{n-1}{2}$. We thus have:

¹⁷ For the binomial approximation to the Poisson binomial, see Ehm (1991). But note that we are not much concerned about the accuracy of the approximation of $\mathbb{E}(\omega_{n-1})$ because we are interested only in the direction of its convergence and not in the rate of its convergence.

$$\mathbb{E}(\omega_{n-1}) = \begin{cases} \sum_{k=\frac{n}{2}}^{n-1} \binom{n-1}{k} p^k (1-p)^{n-1-k} & (n \text{ is even}) \\ \sum_{k=\frac{n+1}{2}}^{n-1} \binom{n-1}{k} p^k (1-p)^{n-1-k} + \frac{1}{2} \cdot \left\{ \binom{n-1}{\frac{n-1}{2}} p^{\frac{n-1}{2}} (1-p)^{\frac{n-1}{2}} \right\} & (n \text{ is odd}) \end{cases}$$

With the approximation, it is easy to see that $\mathbb{E}(\omega_{n-1})$ converges to one of three values:

1, $\frac{1}{2}$, or 0.

$$\lim_{n \rightarrow \infty} \mathbb{E}(\omega_{n-1}) = \begin{cases} 1 & p > \frac{1}{2} \\ \frac{1}{2} & p = \frac{1}{2} \\ 0 & p < \frac{1}{2} \end{cases}$$

The convergence of $\mathbb{E}(\omega_{n-1})$ is more obvious if we approximate $\mathfrak{B}(n, p)$ by a normal distribution as follows.

$$\mathbb{E}(\omega_{n-1}) = \Pr(X \geq Z) = \Pr\left(X \geq \sqrt{n-1} \frac{\frac{1}{2} - p}{\sqrt{p(1-p)}}\right) \quad (\text{A1})$$

where $p = \frac{\sum_{i=1}^{n-1} P_i}{n-1}$ and Z is a standard score. However, as p is a variable that depends on other parameters, it is important to check the conditions under which p converges to $\frac{1}{2}$ and therefore $\mathbb{E}(\omega_{n-1})$ converges to $\frac{1}{2}$. To begin with, let us find conditions under which

we have $\mathbb{E}(\omega_u) \approx \mathbb{E}(\omega_{u+v})$ for sufficiently large integers u and v . $\mathbb{E}(\omega_u) \approx \mathbb{E}(\omega_{u+v})$ implies that we have

$$Z_{u+v} - Z_u = \sqrt{u+v} \frac{\frac{1}{2} - p}{\sqrt{p(1-p)}} - \sqrt{u} \frac{\frac{1}{2} - p}{\sqrt{p(1-p)}} \approx 0 \quad (\text{A2})$$

where Z_k is a standard score when $n = k$. For (A2) to hold with sufficiently large integers u and v , we should have $p = \frac{\sum_{i=1}^{u+v} P_i}{u+v} = \frac{\sum_{i=1}^u P_i}{u} \approx \frac{1}{2}$ where u and v are sufficiently large numbers. In this case, it is required that we have $P_{u+v} = P_u \approx \frac{1}{2}$. To see this through contradiction, suppose that we have $P_{u+v} = P_u = k \neq \frac{1}{2}$, and $\frac{\sum_{i=1}^{u+v} P_i}{u+v} = \frac{\sum_{i=1}^u P_i}{u} \approx \frac{1}{2}$. Then we have:

$$\frac{\sum_{i=1}^{u+v} P_i}{u+v} = \frac{1}{u+v} \left(u \frac{\sum_{i=1}^u P_i}{u} + vk \right) = \frac{1}{u+v} \left(u \frac{1}{2} + vk \right) \neq \frac{1}{2}$$

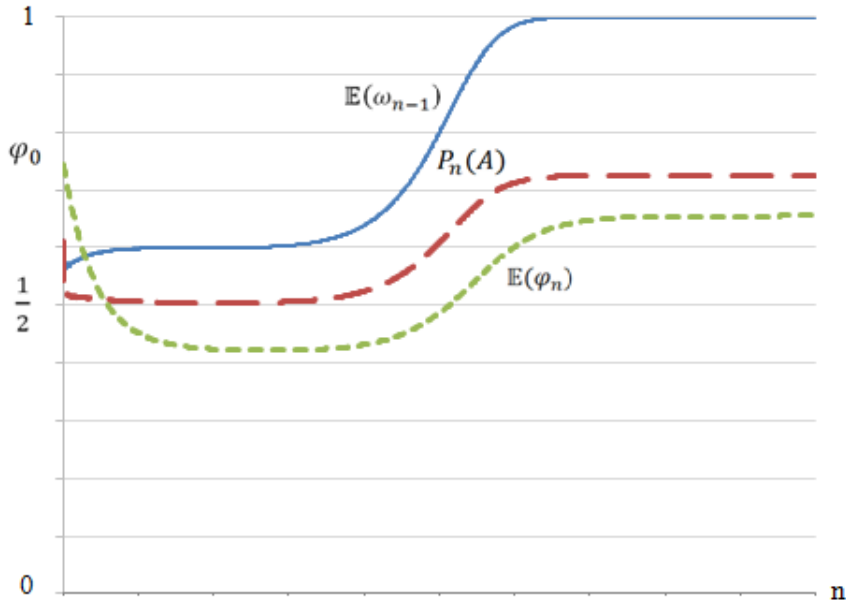
Therefore, for the system to be stable for $n \in [u, u+v]$ where u and v are sufficiently large integers, we should have the following two conditions met.

$$\frac{\sum_{i=1}^{u+v} P_i}{u+v} = \frac{\sum_{i=1}^u P_i}{u} \approx \frac{1}{2} \quad (\text{Condition 1})$$

$$P_{u+v} = P_u \approx \frac{1}{2} \quad (\text{Condition 2})$$

However, these two conditions do not guarantee $\lim_{n \rightarrow \infty} \mathbb{E}(\omega_{n-1}) = \frac{1}{2}$. It is possible that $\mathbb{E}(\omega_{n-1})$ stays stable at a number between zero and one for $n \in [u, u + v]$, then diverges again to either one or zero, as shown in Figure A1. This suggests that a “tipping point”, where a stable $\mathbb{E}(\omega_{n-1})$ suddenly starts to increase, exists if Θ is close to $\tilde{\Theta}$.

FIGURE A1: An Example of Temporarily Stable System



Now let us find conditions, required in addition to (Condition 1) and (Condition 2), under which we have $\lim_{n \rightarrow \infty} \mathbb{E}(\omega_{n-1}) = \frac{1}{2}$. To make our analysis tractable, suppose that $\xi = 1$ holds.¹⁸ In this case, from Equations (1) and (7), notice that $P_n = \mathbb{E}(\varphi_n)$ holds for $n \geq 1$.

$$\mathbb{E}(\varphi_n) = P_n = \alpha \mathbb{E}(\varphi_{n-1}) + (1 - \alpha)\beta \mathbb{E}(\omega_{n-1}) + (1 - \alpha)(1 - \beta)\Theta$$

¹⁸ However, the same analysis holds for a general case of $\xi_A \neq \xi_B$.

Thus Equation (1) becomes:

$$P_n = \alpha P_{n-1} + (1 - \alpha)\beta \mathbb{E}(\omega_{n-1}) + (1 - \alpha)(1 - \beta)\Theta$$

Now let us define initial parameters φ_0 , ω_0 , and Θ ,

$$\varphi_0 = \frac{1}{2} + \frac{k}{\alpha} \quad \text{and} \quad \omega_0 = \Theta = \frac{1}{2}$$

We then have $P_1 = \frac{1}{2} + k$. Then define a function $f_n(k)$ as follows:

$$\begin{aligned} \mathbb{E}(\omega_n) &= \frac{1}{2} + f_n(k) \\ f_n(k) &= \mathbb{E}(\omega_n) - \frac{1}{2} = \Pr\left(X \geq \sqrt{n} \frac{\frac{1}{2} - p_n}{\sqrt{p_n(1-p_n)}}\right) - \frac{1}{2} \quad \text{for } n \geq 1 \end{aligned}$$

where $p_n = \frac{\sum_{i=1}^n P_i}{n}$. It is important to note that $f_n(k) = 0$ holds if $k = 0$. To see this, it is obvious that $f_1(k) = 0$ if and only if $k = 0$, because we have $P_1 = \frac{1}{2} + k$. Given this, we have $f_2(k) = 0$ if and only if $k = 0$. Iterating this process, we know that $f_n(k) = 0$ holds if and only if $k = 0$. Now let us express P_n and p_n as functions of k and $f_n(k)$.

$$P_1 = \frac{1}{2} + k$$

$$P_n = \frac{1}{2} + \alpha^{n-1}k + \sum_{i=1}^{n-1} (1 - \alpha)\beta \alpha^{n-1-i} f_i(k) \quad \text{for } n \geq 2$$

$$\rho_n = \frac{1}{2} + \frac{1}{n} \sum_{j=1}^n \alpha^{j-1} k + \frac{1}{n} \sum_{j=2}^n \sum_{i=1}^{j-1} (1-\alpha) \beta \alpha^{j-1-i} f_i(k)$$

Thus, to have $\lim_{n \rightarrow \infty} \mathbb{E}(\omega_{n-1}) = \frac{1}{2}$, we should have $\rho_n = \frac{1}{2}$ which holds if and only if $k = 0$. To see that $k = 0$ is a necessary and sufficient condition, first notice that P_n is a weighted average of Θ , P_{n-1} , and $\mathbb{E}(\omega_{n-1})$. Then note that $\mathbb{E}(\omega_{n-1})$ is greater than $\frac{1}{2}$ as long as $P_k > \frac{1}{2}$ for any $k \leq n-1$. By contradiction, suppose that $k > 0$ and $\rho_n = \frac{1}{2}$ holds. Starting from $n = 2$, $P_2 > \frac{1}{2}$ holds as $P_1 > \frac{1}{2}$ and $\mathbb{E}(\omega_1) > \frac{1}{2}$. Then, $P_3 > \frac{1}{2}$ holds as $P_2 > \frac{1}{2}$ and $\mathbb{E}(\omega_2) > \frac{1}{2}$. Iterating this process, we have $P_n > \frac{1}{2}$ for any n , which obviously contradicts $\rho_n = \frac{1}{2}$. The same logic applies to $k < 0$, and therefore if $\rho_n = \frac{1}{2}$, then $k = 0$.

The analysis so far has shown that we should have $k = 0$ and therefore $\varphi_0 = P_1 = \frac{1}{2}$.

The same analysis applies to ω_0 and Θ , from which we get $P_1 = \varphi_0 = \omega_0 = \Theta = \frac{1}{2}$.

Then, it is easy to show

$$P_1 = P_2 = P_3 = \dots = P_{n-1} = \frac{1}{2} \quad (\text{Condition 3})$$

In addition, the equilibrium condition in Equation (8) should also hold. With

$\lim_{n \rightarrow \infty} \mathbb{E}(\omega_{n-1}) = \frac{1}{2}$ and (Condition 3), the Equation (8) becomes:

$$(1 - \beta) \left(\frac{1}{2} - \Theta \right) = 0 \quad (\text{Condition 4})$$

PROPOSITION A1: Taken altogether, we have

$$\lim_{n \rightarrow \infty} \mathbb{E}(\omega_{n-1}) = \begin{cases} 1 & p > \frac{1}{2} \\ \frac{1}{2} & (\text{Conditions 1 - 4}) \\ 0 & p < \frac{1}{2} \end{cases}$$

Proposition A1 can be extended to Proposition A2.

PROPOSITION A2 : Under mild assumptions on the values of α , β , and $\varphi_0 > \frac{1}{2}$,

$\lim_{n \rightarrow k} \mathbb{E}(\omega_{n-1}) = 1$ holds when $\Theta \geq \frac{1}{2}$ and $\lim_{n \rightarrow k} \mathbb{E}(\omega_{n-1}) = 0$ holds when $\Theta = 0$.

PROOF:

Suppose $\Theta > \frac{1}{2}$, meaning the first mover is also better in terms of quality. To see that $\mathbb{E}(\omega_{n-1})$ is increasing with n , and $\lim_{n \rightarrow k} \mathbb{E}(\omega_{n-1}) = 1$ holds, let me first define a cumulative binomial function, \mathbb{B}_{n-1} , where the number of successes is greater than one half of the number of total trials¹⁹.

¹⁹ If the number of trials is an even number and we have equal number of successes and failures, I assume that the event ω_{n-1} happens with probability $\frac{1}{2}$.

$$\mathbb{B}_{n-1} = \begin{cases} \sum_{k=\frac{n}{2}}^{n-1} \binom{n-1}{k} \Theta^k (1-\Theta)^{n-1-k} & (\text{n is even}) \\ \sum_{k=\frac{n+1}{2}}^{n-1} \binom{n-1}{k} \Theta^k (1-\Theta)^{n-1-k} + \frac{1}{2} \cdot \left\{ \binom{n-1}{\frac{n-1}{2}} \Theta^{\frac{n-1}{2}} (1-\Theta)^{\frac{n-1}{2}} \right\} & (\text{n is odd}) \end{cases}$$

\mathbb{B}_{n-1} can be considered the probability that website A will show up as “the more popular website”. This is for the case when website A is chosen more than half the time from a binomial distribution of $n - 1$ trials with success probability Θ . But as $P_n(A) > \Theta > \frac{1}{2}$ holds, it is easy to see that $\mathbb{E}(\omega_{n-1}) > \mathbb{B}_{n-1}$ holds for any n . \mathbb{B}_{n-1} goes to 1 as n increases²⁰, and so does $\mathbb{E}(\omega_{n-1})$.

Then suppose that $\Theta = 0$. Under mild assumptions on parameters (i.e., if α and β are not too large), then we have $\lim_{n \rightarrow \infty} \mathbb{E}(\omega_{n-1}) = 0$. The proof for the case when $\Theta = \frac{1}{2}$ follows from Proposition A.1; if neither the first mover nor the second has an advantage in quality, i.e., $\Theta = \frac{1}{2}$, then $\mathbb{E}(\omega_{n-1})$ goes to 1 as n goes to infinity, as long as $\varphi_0 > \frac{1}{2}$ holds. The fact that $\lim_{n \rightarrow \infty} \mathbb{E}(\omega_{n-1})$ can only be either 1 or 0 suggests there is a “cutoff” Θ between 0 and $\frac{1}{2}$, which is defined in Definition 1.

²⁰ For an intuitive explanation, suppose that 51% of the whole population is “website A lovers” and that randomly chosen individuals always choose their preferred website. In this case, if the more popular website is selected based on the choice made by one randomly selected person, then website A will have a 51% chance to be selected. However, if the more popular website is selected based on the choice made by a large population, for example several million, then website A will almost always be chosen by more than half of the population and be selected as “the more popular website”.

Appendix 2.C: DATA

The dependent variable comes from Naver's public dataset of “*the most popular news*,” which is compiled both daily and weekly. Daily data has been archived since April 2004, and weekly data since June 2005. I use weekly ranking data because they are more comparable with my *weekly* independent variable. The dataset has ranked the top thirty *most viewed news* every week since June 2005, with the cutoff for the ranking every Friday at midnight. Naver's weekly ranking is collected separately for eight different sections: politics, business, social, cultural, world, science, sports, and entertainment. I leave out the sports and entertainment news sections as the theoretical model does not have any clear prediction for them. Data is all publicly available for replication and detail information on the data is as follows.

Variables	Type	Coverage	Data Source
Unique visitors to Naver	Weekly	June 2005 - June 2010	Nielson Korea (http://www.koreanclick.com)
“Direct” traffic to Yonhap relative to the “direct” traffic to all news organizations supplying news stories to Naver combined.	Weekly	June 2005 - June 2010	Nielson Korea (http://www.koreanclick.com), and Naver ²¹
Naver's most viewed news	Weekly	June 2005 - June 2010	Naver ²²
Asset size of newspaper companies	Yearly	2005 - 2010	Media Statistics Information System (http://mediasis.kpf.or.kr/)

²¹ For the period after December 2008, the “direct” traffic for each site is obtained by removing the traffic referred by Naver from the total online traffic for each site.

²² <http://news.naver.com/main/ranking/popularWeek.nhn>

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CHAPTER 3:

COMPARISONS OF VARIOUS ONLINE INSTITUTIONS:

INFORMATION CONSUMPTION ON SOCIAL MEDIA

3.1. INTRODUCTION

Today, the Internet is a major source for people to obtain new political information. According to a survey conducted by Pew Internet (2010), the Internet has surpassed newspapers in terms of popularity as a news platform by a substantial margin, and ranks behind only television. Further, the Pew Internet survey summarizes that “peoples’ relationship to news is becoming portable and participatory.” The survey found that 33% of mobile phone owners read newspapers on their mobile phones, and 37% of Internet users disseminate news content via postings on social media sites such as Facebook or Twitter. The rapidly growing number of people that use mobile technologies to read news online (Pew Internet, 2010) suggests that news organizations will have to increase their use of social media to attract attention online,¹ In response to the changing business environment, many media organizations have adopted social media to drive traffic to their websites (Messner et al., 2011).² For instance, *The New York Times* describes its social media marketing as “one of the several essential strategies for disseminating news online” (Emmett, 2009).

¹ Recent evidence implies that people who read newspapers on their mobile phones tend to be more active users of social media sites and read or share news stories more frequently using those sites (Pew Internet, 2009). Rupert Murdoch, News Corp’s chief executive has referred to mobile technologies as a “game-changer” for news consumption (Reuters, Nov. 12, 2010).

² See Table 3.1.

TABLE 3.1: Newspapers' social media adoption

Facebook _A (%)	Facebook Supporters _B	Twitter _C (%)	Twitter Supporters _D	Tweets Per Week _E
82.6	10,591	84.7	22,070	116

A The percentage that had a Facebook account in January, 2011

B Average number of people who said that they liked the Facebook page as of January, 2011

C The percentage that had a Twitter account in January, 2011

D Average number of followers as of January, 2011

E Average number of tweets sent per week since adoption as of January, 2011

Despite the rapidly growing use of social media in the newspaper industry, thus far, very few studies have discussed the impact of social media on the diversity of information in the context of online news. Thus, an important question is whether, and to what extent, adoptions of social media tools have a potential to have different impacts on the diversity of online information than other online institutions such as search engines or news aggregators have. There are at least two reasons why the online attention generated by social media sites might differ from that generated by search engines or news aggregators.³ (1) Social media sites generally do not *rank* online news stories. Search engines or news aggregators create cascades⁴ because they *rank* information depending on certain measures of “popularity” (Duan et al., 2008); information with a higher rank is more visible to users and has an even higher probability of getting online clicks.⁵ (2) Social media sites provide a platform for

³ See Chiou and Tucker (2010) for empirical evidence of the impact of news aggregators on the number of visitors to newspaper sites.

⁴ A cascade (information cascade, in this case) arises when people who have imperfect information about true product value infer value by observing the choices of others (Banerjee, 1992; Bikhchandani et al., 1992).

⁵ See Salganik et al. (2006) and Tucker and Zhang (2011) for evidence on the impact of popularity information.

organizations to *reach out* to their audiences. For example, before the advent of social media tools, news organizations would post their news stories on their websites and depend on search engines or aggregators to direct online traffic to them. Now, news organizations make use of social media tools to actively disseminate news: these tools ensure that news reaches all the networks⁶ that expressed an interest in the news, regardless of whether search engines or aggregators pay attention to that news. The above two differences suggest that the online attention generated by social media sites might be more egalitarian than that generated by other online institutions.

3.2. DATA

This chapter presents empirical evidence on the association between social media adoptions and online news readership. I conducted two empirical analyses. The first is a test of the association between online traffic to newspaper sites and the news organizations' adoption of Twitter. The second is a comparison of the online traffic generated by different online institutions: search engines, news aggregators, and social media. The following subsections explain how the data set for each empirical analysis is constructed. Summary statistics of all variables can be found in Table 3.2.

3.2.1. ONLINE TRAFFIC

This paper uses online traffic as a proxy for the online attention or readership. Among the various measures of online traffic, I used the measure involving the number of

⁶ The concepts of “friends” on Facebook and “followers” on Twitter.

unique visitors. I compiled monthly online traffic data sets for 337 daily newspapers, from January 2007 to December 2010. Monthly online traffic data for 2007 were obtained from ComScore, Inc, and the data for the later periods were purchased from Compete, Inc., and the data from two different sources were appended.⁷ The studied sample of newspapers (337) includes almost all the major newspapers in the US, except for community newspapers and those without websites.⁸ The earliest adopters joined Twitter in March 2007. Therefore, my observation included the time before (from January to March 2007) and after Twitter adoption for all the newspapers in the sample.

TABLE 3.2: Summary Statistics

Variable	Mean	Std. Dev.	Min	Max
UV_{it} (Log-transformed)	12.0	1.3	4.7	17.1
Direct traffic	17,216	52,603	529	1,488,239
Social media traffic	31,664	84,790	726	1,469,476
Search traffic	117,376	334,915	955	3,728,630
Aggregators traffic	23,700	59,858	249	787,092
Number of Twitter followers	22,070	228,414	0	3,809,821
Number of tweets	12,310	12,531	0	94,198
Number of months passed since Twitter adoption at the time of January, 2011	24	13	0	49

• Note: “Number of months passed since Twitter adoption at the time of January, 2011” is the maximum value of $adopt_{it}$ in equation (1) for each newspaper.

⁷ Monthly online traffic data set was obtained from two different sources as the data from Compete, Inc. was not available for 2007

⁸ I excluded from the analysis the newspapers for which the unique visitor information could not be identified. For example, some newspapers in Michigan were excluded because they share a website (www.mlive.com) and do not maintain individual ones.

The monthly online traffic data can be disaggregated into the following five sub-categories based on the sites people visit prior to visiting the newspaper website: *direct traffic*, *search traffic*, *aggregators' traffic*, *social media traffic*, and *others*. As explained in Chapter 1, *Direct traffic* refers to online traffic that is not referred by any other websites. For instance, if you directly visit the *New York Times* website by typing *www.nytimes.com* into the web address bar, then this type of traffic will be classified under *direct traffic*. *Search traffic*, *aggregators' traffic*, and *social media traffic* are also defined as in Chapter 1; they refer to online traffic that is referred by search engines, news aggregators, and social media websites, respectively. Social media sites with the largest share of traffic include Facebook and Twitter.

As in Chapter 1, when classifying sub-categories, I paid special attention to the *search traffic* and *direct traffic* categories, and I had to reclassify some of the *search traffic* as *direct traffic*. For example, if you type in the name of a newspaper on the Google search engine bar, even though you will be directed straight to that newspaper's website, this action will be classified under *search traffic*, although, in reality, it is no different from *direct traffic*. Therefore, I collected data on the keywords used by people to search for newspaper websites. If the keywords constituted variants of the name of a newspaper, such as "new york times," "nytimes," or "nyt," I reclassified that traffic from *search traffic* to *direct traffic*.

3.2.2. TWITTER ADOPTION AND THE NUMBER OF "FOLLOWERS"

In order to test whether newspaper sites' sign up for Twitter has been positively

associated with their online readership, I compiled a data set of the number of followers, the number of messages (“tweets”) created on Twitter, and Twitter joining dates for the 337 sample newspapers. The number of followers and the number of messages were collected manually from each newspaper's Twitter account during the last week of January in 2011, and Twitter joining dates were collected using an online application of “when did you join Twitter?”⁹

3.3. METHODOLOGY

3.3.1. NEWSPAPERS’ SOCIAL MEDIA ADOPTION AND ONLINE READERSHIP

In order to facilitate an understanding of the association between social media adoptions and online readerships in online news industry, I present a case study of Twitter. In addition to the association between the two variables, I also discuss how the association depends on the size of the newspapers’ networks and the number of messages posted on Twitter.

Twitter¹⁰ is a particularly interesting networking site because it adopts the “asymmetric model” of relationships (Porter, 2009). Unlike other social media sites like Facebook—where two users can view each other’s posts, provided they mutually agree to exchange information—Twitter enables news organizations to maintain an “asymmetric” position by following only a few chosen accounts, all the while being followed by several million users worldwide (Porter, 2009). This asymmetry makes

⁹ www.whendidyoujointwitter.com

¹⁰ Twitter is a social networking, blogging, and texting platform (Messner et al., 2011) where users can post messages called “tweets,” in under 140 characters, to their audience, referred to as their “followers.” Twitter users can choose who they want to follow.

Twitter an attractive tool by which news organizations can disseminate news. Farhi (2009) observes the growing importance of Twitter, noting that “its speed and brevity make it ideal for pushing out scoops and breaking news to Twitter-savvy readers.”

This paper uses the data for 337 daily newspapers from January 2007 to December 2010 for the empirical test. Specifically, I ran the following regressions.

$$(1) \quad UV_{it} = \alpha_0 + \beta_1 adopt_{it} + f(t) + \alpha_i + \epsilon_{ijt}$$

$$(2) \quad UV_{it} = \alpha_0 + \beta_1 adopt_{it} + \beta_2 adopt_{it} followers_i + f(t) + \alpha_i + \epsilon_{ijt}$$

The dependent variable UV_{it} represents the online traffic measured by the log transformed number of unique visitors to a newspaper site i . UV_{it} is logarithmically transformed to interpret the estimated coefficients in terms of a percentage change. The variable $adopt_{it}$ measures the number of months since newspaper i adopted Twitter. I impose a linear parametric assumption on $adopt_{it}$; If the newspaper has not adopted Twitter, $adopt_{it}$ equals zero, and thus, $adopt_{it}$ is an integer greater than or equal to zero. The variable $followers_i$ is the size of networks on Twitter (the number of “Twitter followers”). I include the newspapers fixed effect, α_i , and control for a nonparametric time trend $f(t)$. Coefficient β_1 represents the estimated impact of the adoption of Twitter on the online readership of newspaper site i , while coefficient β_2 represents an interaction effect between $adopt_{it}$ and $followers_i$. The main effect of $followers_i$ is dropped because of the newspapers fixed effect, α_i .

I also tested equation (2) using the number of messages created on Twitter (the

number of “tweets”) in place of the variable $followers_i$. Although the two variables, the number of “tweets” and followers, are significantly related¹¹, they have an important difference in that the number of “tweets” can be controlled by the Twitter account user while the number of followers cannot. In other words, the more significant the association between the number of “tweets” and online traffic, the greater the potential for news organizations to *reach out* to their audiences online. However, it is indeed difficult to disentangle the impacts that the two variables have on online traffic, and this paper does not aim to do so. Rather it presents descriptive associations between the variables.

3.3.2. COMPARISON OF ONLINE TRAFFIC GENERATED BY DIFFERENT ONLINE INSTITUTIONS

The results estimated with equations (1) and (2) provide an estimated associations between newspapers' Twitter adoptions and their online readerships. Although these results provide an empirical evidence of Twitter adoptions in online news industry, an important question remains; is the estimated association above any *different* from the associations between other online institutions and online attention? In fact, there have been some theoretical models (Athey et al. 2011; George and Hogendorn 2011; Dellarocas et al. 2011; Bar-Isaac et al. 2011) on the impacts of online institutions such as search engine and news aggregators, no previous studies have answered whether the associations between different online institutions and online traffic are significantly different. The second part of this paper aims to provide a descriptive

¹¹ Binary regression between the two variables have a positive coefficient significant at 1%.

evidence to shed light on this question.

In order to differentiate between the online traffic generated by different online institutions, I obtained the total online traffic the newspapers received. Depending on the method of search and the online institutions that directed traffic to the newspaper sites, I further disaggregated this online traffic into direct traffic, search traffic, aggregators' traffic, and social media traffic. When comparing online traffic, I focused on the concentrations of the different institutions within the online news industry by presenting Lorenz curves¹² of the online traffic generated by each online institution. For this comparison, I used a cross-sectional data set of January 2011. These details are presented in Figure 3.1. Furthermore, to test whether the presented Lorenz curves are statistically different from each other, I conducted K-S tests, the details for which are presented in Table 3.3.

3.4. RESULTS

3.4.1. NEWSPAPERS' SOCIAL MEDIA ADOPTION AND ONLINE TRAFFIC

Table 3.3 present the estimated coefficients from equations (1) and (2). The first column represents the impact of Twitter adoption on newspapers' online readership. As can be seen, newspapers' Twitter adoptions have had a positive impact on attracting readerships to their websites. Newspapers' Twitter adoptions were associated with an additional one percent increase in online readership each month

¹² A Lorenz curve is a graphical representation of the cumulative distribution of the empirical probability distribution. Each point on the curve represents a statement such as “the bottom x percent of all newspapers have y percent of the total market shares.” Therefore, the closer the Lorenz curve to a 45 degree line, the less concentrated is the underlying online traffic.

after the adoptions. However, the second column shows that this association might not be constant over time; the association between Twitter adoptions and online readership is the strongest when newspapers just adopted Twitter, but the association decreases over time.

TABLE 3.3: The impact of newspapers' Twitter adoptions on their online traffic

	Dependent variable: UV_{it}			
	(1)	(2)	(3)	(4)
<i>adopt</i>	0.011** (2.60)	0.019** (2.26)	-0.002 (-1.57)	-0.003 (-0.37)
<i>adopt</i> ²		-0.0002** (-2.19)		
<i>adopt</i> × <i>followers</i>			0.0221** (2.55)	
<i>adopt</i> × <i>tweets</i>				0.011** (2.01)
<i>Newspaper fixed effect</i>	Yes	Yes	Yes	Yes
<i>Time fixed effect</i>	Yes	Yes	Yes	Yes
<i>N</i>	12,306	12,306	12,306	12,306

1. Unit: followers in millions, tweets in ten thousand

2. *t* statistics in parentheses, * $p < 0.10$, ** $p < 0.05$

The third column tests whether the association observed in the first column is affected by the size of online networks on Twitter. As can be seen in the third column, the estimated association between newspapers' Twitter adoptions and their online readership is negative (i.e. coefficient β_1 in equation (2) is negative) when the number of followers is assumed to be set as zero, although the coefficient is not statistically significant. The interaction term between the variable $adopt_{it}$ and the number of followers is positive and statistically significant, which suggests that the

association between the two variables increases in the size of online networks on Twitter. Considering the large variation in the number of Twitter followers, as can be seen in Table 3.1, this evidence suggests that the estimated association between Twitter adoptions and online readership might heavily depend on the size of online networks.

A similar analysis was conducted in column 4, in which I used the number of tweets message created on Twitter in place of the number of Twitter followers. In column (4), I obtained a similar result as in column (3). The result suggests that the estimated association might be minimal for newspapers that have a small number of tweets while the association is significantly positive for those with a large number of tweets. The fact that the results with the number of followers and tweets are similar is not a surprise given the fact that the two variables (the number of followers and tweets) have a significant positive correlation; on average, newspapers with a large number of followers on Twitter tweet more frequently than those with a small number of followers.

3.4.2. COMPARISON OF ONLINE TRAFFIC GENERATED BY DIFFERENT ONLINE INSTITUTIONS

I now report the results of the comparisons of online readership generated by different online institutions (Figure 3.1 and Table 3.4). Figure 3.1 shows the Lorenz curves for *direct traffic*, *social media traffic*, *aggregators' traffic*, and *search traffic*. It can be seen that *direct traffic* is the least concentrated, while *search traffic* is the most highly concentrated. *Social media traffic* and *aggregators' traffic* lie somewhere in between,

though *social media traffic* is less concentrated than *aggregators' traffic*. Table 3.4 presents the results of the K–S tests. As seen here, the observed differences in the Lorenz curves are statistically significant.

FIGURE 3.1: Lorenz curves of online traffic by online institutions

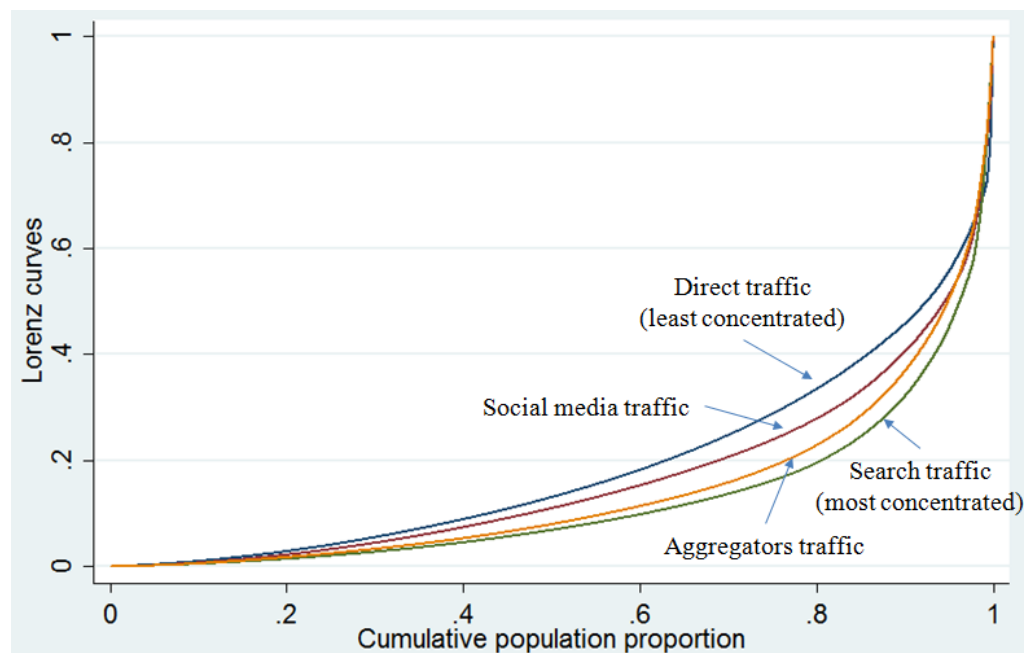


TABLE 3.4: The Kolmogorov-Smirnov (K-S) Tests

Comparison Groups	Coefficient D	P-value	Corrected
Social media vs. Direct traffic	0.246	0.000	0.000
Social media vs. Search traffic	0.431	0.000	0.000
Social media vs. Aggregators traffic	0.310	0.000	0.000

Direct traffic may be regarded as a proxy for what the total traffic would have been without search engines and news aggregators. *Social media traffic* is less concentrated than *search traffic* or *aggregators' traffic* probably because of the two

reasons proposed in Section 2—social media sites generally do not rank information and they provide a platform for news organizations to reach out to their audiences. However, *social media traffic* is still more concentrated than *direct traffic*, suggesting that information within social media sites might be still susceptible to cascades to some extent. For instance, even though you are only following your local, regional newspaper on Twitter, and not *The New York Times*, people whom you follow are more likely to recommend to you an article from *The New York Times* compared to an article from your local newspaper. In this case, even though you are not directly following *The New York Times*, you are likely to click on the *New York Times* article.¹³ This process could result in the higher concentration of *social media traffic* compared to *direct traffic*.

3.5. CONCLUSION & LIMITATIONS

This study estimated an association between newspapers' Twitter adoption and their online readership. I present evidence of a positive association between the two variables, and observe that the association increases in the size of online networks created in social media. Considering the large variations in the size of online networks, as can be seen in Table 3.1, and previous evidence (e.g. Schlozman et al. 2012) that find a highly concentrated distribution of the size of social media networks among social media adopters, the evidence may indicate that the estimated association might heavily depend on the size of online networks in social media. Then, in order to see whether the online readership generated by social media sites

¹³ As a result, you are more likely to follow *The New York Times* as well.

differs from that generated by other online institutions, I compare the distributions of online readership generated by social media sites, search engine, and news aggregators. *Social media traffic* was less concentrated compared to the traffic generated by search engines or news aggregators, but; it was more concentrated than *direct traffic*. A possible answer for this observation might be that social media traffic is less susceptible to cascades than search engines or news aggregators, although not entirely protected from cascades.

However, it is important to be clear that the observed coefficients in equations (1) and (2) show descriptive associations rather than causal impacts of Twitter adoptions. For equations (1) and (2) to yield an unbiased and consistent estimate, one critical assumption has to be made: newspapers' adoption of Twitter is independent of any idiosyncratic shocks on online traffic. In other words, after controlling for the factors that affect online traffic, such as newspaper quality or time trends, the treatment (i.e., newspapers' Twitter adoption) must be random across newspapers; that is, it should be uncorrelated with any omitted variables that impact online traffic, which is indeed a strong assumption. For example, a possible omitted variable that might still bias the estimates is the newspapers' adoption of other social media sites. It is highly possible and likely that news organizations will adopt Facebook at the same time at which they adopt Twitter. In this case, the estimated coefficients in equations (1) and (2) may be overestimated, and we should interpret these coefficients as the association between online news traffic and social media adoptions, in general, rather than Twitter adoptions in particular.

The second analysis with Lorenz curves also has its limitations. The presented

evidence aims to highlight the differences between the online traffic generated by social media sites and that generated by other online institutions. However, although useful, the evidence is a descriptive rather than an analytical empirical analysis, and thus does not show a clear association between social media adoptions and online traffic. For example, the analysis does not estimate the potential substitutions among different online institutions. In other words, when a newspaper adopts a social media site, this site will direct traffic to the newspaper site; this is called *social media traffic* in this paper. However, it may also crowd out some *direct traffic* or traffic that is directed by other online institutions.¹⁴ Therefore, it is possible that newspapers' adoption of social media tools would have a smaller impact on their online traffic than what the result of this study suggests.

Furthermore, like other studies estimating the impact of social media, the analysis in this study is also based on observations that I collected when the Internet and social media were still in their "adolescence" (Hindman, 2009). It is important to emphasize that the time periods covered in this study might not be reflective of the full impact of social media, as some studies have pointed out (Schlozman et al., 2010; Bimber, 2008).

Nevertheless, this chapter is the first empirical evidence, to the best of my knowledge, that sheds light on the association between social media adoptions and online readership in online news industry and the different implications that different online institutions may have on the distribution of online readership. The association is estimated to be significantly positive and to increase in the size of online networks

¹⁴ Evidence of substitutions among different online institutions is rare. However, previous studies have estimated substitutions between online and offline newspapers (Gentzkow, 2007; George, 2008; Filistrucchi, 2005) and between online and offline advertising channels (Goldfarb and Tucker, 2011).

created on social media sites. A descriptive evidence suggests that the association between social media adoptions and online readership is different from the associations between other online institutions and online readership.

3. 6. REFERENCE

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CHAPTER 4:

SOCIAL MEDIA, CAMPAIGN FINANCE, AND DEMOCRACY

4.1. INTRODUCTION

4.1.1. THE RECENT ADOPTIONS OF SOCIAL MEDIA IN POLITICS

The recent advent of new information technology, along with the resulting social media—such as Facebook and Twitter—and its enthusiastic use in political competition, has rekindled attention on the role of new information technology in politics. Currently, almost every major American politician has a Twitter¹ account, and many employ specific staff or even social media consulting firms to maintain such accounts. One example of a politician who has used social media to the utmost is Barack Obama, who utilized Twitter to hold America’s first virtual presidential town hall meeting in July 2011. During this event, he responded via his official Twitter account to questions posted online by users of social networking services, including the chair of the Republican National Committee, Reince Priebus. Many commentators described the event as a modern “Kennedy-Nixon TV debate moment” that would foreshadow the future use of media in politics. Weeks later, the president used Twitter during the debt ceiling debate to mobilize his 9.4 million followers and asked them to “tweet at your Republican legislators and urge them to support a bipartisan compromise to the debt crisis.” The growing importance of Twitter in

¹ Twitter is an online social networking and microblogging service that enables its users to send and read text-based posts of up to 140 characters, known as “tweets.” The service has rapidly gained worldwide popularity, with over 300 million users as of 2011 (Taylor, 2011), generating over 200 million tweets (Twitter, 2011).

politics is also evinced by that fact that in October 2010, former House Majority Leader Nancy Pelosi made her initial announcement that she would run for House Minority Leader not on a major news network, but via Twitter.²³

Politicians' recent active adoption of the new information technology raises an important question: Are politicians deriving measurable benefits from their social media adoptions, and if so, to what extent? Presumably, politicians have embraced this new form of communication technology because they find it effective for communicating with their supporters; therefore, it is reasonable to expect that significant benefits are associated with their use of social media. A few studies have attempted to report the potential effects of politicians' use of social media. For instance, a body of literature provides descriptive evidence that online attitudes, as measured through the sentiments of "tweets," correlates well with public sentiment as measured through polls (Tumasjan et al. 2010) and that the size of politicians' online networks (e.g., the "friend" count of politicians' Facebook accounts) is an acceptable predictor of public opinion (Wattal et al. 2010; Williams and Gulati 2007).⁴

While previous studies have focused on social media use by politicians in general, no study, to the best of my knowledge, has empirically investigated this

² CongressDaily 11/5/2010, p1-1

³ Twitter use has also spread globally to other democracies. The newly elected president of Chile, Sebastián Piñera, recently asked his cabinet members to start using the social networking tool. Other studies have reported that the number of Japanese politicians using Twitter grew from only 3 to 485 in less than a year and that 577 German politicians had opened Twitter accounts.

⁴ Another body of work reports some evidence of the impact of the Internet or new media in general, rather than focusing on the impact of only the social media. Some studies find that the dominance political elites normally enjoy is reproduced or even magnified on the Internet (Hindman 2008, Schlozman et al. 2012), which challenges the optimistic view that the Internet will promote a democratic public sphere that reduces inequalities of attention between elites and those outside the political mainstream (Agre 2002; Benkler 2006; Bennett & Entman 2002; Gillmore 2004; Jenkins 2006). Others report that new media may polarize public opinion (Prior 2007; Sunstein 2007; Baum & Groeling 2008).

phenomenon in the context of election campaigns, even though elections are important political activities. Thus, the present research attempts to fill this gap in our understanding of the political use of the social media tool, Twitter, by presenting an empirical test of the association between politicians' social media adoption and the success of their campaign financing activities, and how this association differs among politicians with different online network sizes (e.g., Twitter followers) and varying political ideologies.

4.1.2. COMPETING HYPOTHESES: MINIMAL VS. STRONG EFFECTS

Since the advent of radio and television, researchers have hotly debated the effect of new technologies on election campaigns. One school of researchers (Klapper 1960; Campbell et al. 1960) follow the famous “minimal effects” thesis, which argued, among other things, that political campaigns mediated by information technology only marginally affect public opinion. Katz and Lazarsfeld (1955) provided a theory supporting this finding—namely, the “two-step flow of communication”—positing that media messages are filtered by opinion leaders through social mediation processes. This theory was largely based on social conditions at that time (Bennett & Iyengar 2008), which were characterized by (1) a pre-mass-communications media system and (2) a group-based society with social capital (Putnam 2000). Opposing this theory, however, is another school of thought that has emerged since the 1980s, with such underlying social changes as individuals' disconnection from a group-based civil society (Bennett & Iyengar 2008) and better measurements of priming, framing, and agenda setting. Numerous studies belonging to this school have suggested that

television news could actually determine which issues the public considers important (Iyengar, Peters, & Kinder 1982) and that public opinion toward policies could be significantly influenced by the content of news stories (Iyengar & Kinder 1987; Gilliam & Iyengar 2000; Baum 2005; Gentzkow 2006; Gerber, Karlan, & Bergan 2009).⁵

However, the emergence of new media, such as cable television and the Internet, has led to a new era, in which media may play a different role in political campaigns (Bennett & Iyengar 2008). The emergence of new media has created a much wider range of media choices; therefore, politicians are no longer able to reach vast audiences via a limited number of channels. Supporting this statement, Jenkins (2006) has shown that unlike advertisers in the 1960s, who could reach 80% of U.S. women with a prime-time spot on ABC, CBS, and NBC, modern advertisers have to run the same spot 100 TV channels to reach the same number of viewers. Based on this observation, some scholars argue that we may again return to a time of minimal effects (Bennett & Iyengar 2008).

In this study, however, I argue that new media, such as the Internet, will still have a significant impact with the rise of a “self-selected” audience as opposed to a more “inadvertent” audience during the heyday of network news. Although political information in a prime-time spot on three networks would have reached a greater audience before, most members of that audience were inadvertent and less likely to change their positions in response to the information provided (Negroponte 1995, Sunstein 2007; Prior 2007; Bennett & Iyengar 2008). With a large number of media outlets, however, people can now self-select the political information that matches

⁵ Also see Stromberg (2004), Gentzkow and Shapiro (2004), and DellaVigna and Kaplan (2007).

and reinforces their ideological positions. This fragmented audience structure allows political elites to influence public opinion through targeted use of new information technologies, even though the size of their audience may be smaller.

In order to test these competing hypotheses, the first consideration should be the possible effect of “self-selective” technology. Previous evidence (Chapters 1-3) suggests that online technology, such as social media, may *concentrate* and *polarize* information consumption patterns through a cascade mechanism. Previously, without online technology, people had limited chances to *interact* or *network* with nonlocal politicians, while they can now have a personal conversation with nonlocal candidates by “following” or “friending” them. Out of the large number of nonlocal politicians, people are more likely to “follow” or “friend” the ones they perceive as more *salient* (Chapter 1, Farrell & Drezner 2008), that is, either *nationally recognized* or *ideologically distinctive*. Hence, the preferences revealed by people’s “self-selection” with these technologies might be more concentrated and polarized than what is observable without these technologies. If this online information consumption pattern affects political behaviors, such as people’s willingness to contribute to a political candidate, we should expect increasing *concentration* and *polarization*, not only in online information consumption patterns but also in important political outcomes such as campaign finance.

4.1.3. SOCIAL MEDIA & POLITICAL FINANCE

In examining the effects of new information technology on political outcomes, I investigate the political use of *social media* and its effect on *political finance*. The

political effects of such social media technology as Twitter deserve special attention, not only because most politicians are using them but also because one of the key features of this new technology is to maximize “self-selection,” which is the component that leads us to the two different hypotheses of minimal and strong effects.⁶ Here, I look particularly at Twitter among the many existing forms of social media because its “asymmetric” form of network makes it potentially more conducive to political interaction (Porter 2009, Hong & Nadler 2011).⁷

Political finance, among the many possible political variables, is important for the following reasons. First, recent empirical evidence has increasingly indicated that political finance has a significant and positive impact on candidate electoral success in a number of countries with national, local, and multiparty elections (Benoit and Marsh 2008), regardless of whether the candidates are challengers or incumbents⁸. Second, online technology may have great potential for revolutionizing how politicians raise money for their campaigns, as Obama’s extraordinary success at Internet fundraising in the 2008 presidential election suggests. In 2008, presidential candidates raised more than \$1.6 billion, an increase of more than 149 percent over the amount raised by presidential candidates in 2004. The Internet, along with social media technologies, has often been identified as one of the most important

⁶ Further, previous evidence (Hong 2012) implies that social media technology is an ideal platform for political campaigning as it provides a greater potential for politicians to reach out to their targeted audiences rather than just waiting for search engines to direct traffic to them.

⁷ Twitter differs from many other alternative social media, such as Facebook, in the sense that it enables asymmetric networks. For example, Twitter users (say, a politician) can find him or herself in the “asymmetric” position of following the tweets of a small number of users, while his or her own tweets are followed by 3 million users (Porter 2009). Twitter can thus function as a form of social media that is potentially more conducive to political interaction (Porter 2009).

⁸ There is an ongoing debate over whether the impact of campaign spending is more significant for challengers than for incumbents. The former view is supported by Abramowitz (1988, 1991), Ansolabehere and Gerber (1994), Green and Krasno (1988), Jacobson (1978, 1990), and the latter view by Gerber (1998) and Moon (2006).

contributing factors to the increase in fundraising in 2008 (Weintraub & Levine 2009). Finally, political representation in the United States is often described as “‘surrogate,’ in which citizens are represented by legislators with whom they have no electoral relationship” (Mansbridge 2003, 522), and this surrogate representation is primarily expressed through campaign contributions (Mansbridge 2003, Gimpel et al. 2008).

4.1.4. IN-STATE VS. OUT-OF-STATE DONATIONS

For the purpose of my research, I classify campaign contributions as *in-state* and *out-of-state*. The terms *in-state* and *out-of-state* are defined with reference to the states in the United States and to the fact that a significant number of people do donate to candidates outside their home state. *Out-of-state* implies a state that the politician does not represent, and similarly, *in-state* implies the home state of a politician. I examine the association between political use of social media and political finance separately for *in-state* and *out-of-state* donations for two reasons.⁹

First, and most important, the widespread political use of social media may have different effects on *in-state* and *out-of-state* donations: It is likely to increase the relative importance of *out-of-state* donations compared to *in-state* donations, because contributions to nonlocal candidates are often hampered by information barriers

⁹ An alternative way of conducting the analysis would be to do so at congressional district level. However, in this study, I use state-level rather than district-level observations for two reasons. Most important is that in-state and out-of-state donations may have different implications for the system of representation in the United States, and the boundaries of *states* are the most important geographical unit of political representation. For instance, the U.S. Constitution grants rights of representation in Congress to *states*, not to congressional districts or individual citizens (Rehfield 2005; Gimpel et al. 2008). Further, campaign finance data is observed at the zip code level and the provided zip code areas are, in many cases, split by congressional district boundaries. Thus, the in-state and out-of-state comparison is likely to provide a more robust estimate than a similarly defined in-district and out-of-district comparison.

between individuals and the candidates. Networks formed through social media can reduce these information costs in the following manner: Networks constructed in a non-formal setting through social media technologies may help citizens to learn about the politicians. This knowledge is important because “to become engaged in the fundraising efforts of out-of-district candidates, citizens need to learn about them and come to believe that they will be a sensible investment of campaign dollars” (Gimpel et al. 2008, 375). Further, individuals generally contribute to political campaigns mainly because they are *asked* to do so (Brown, Powell, and Wilcox 1995; Francia et al. 2003; Grant and Rudolph 2002). Their willingness to contribute is greatly affected by social networks formed in a variety of settings (Brady et al. 1999; Cho and Gimpel 2007; Gimpel et al. 2006), which may include the online networks on social media.

Second, the differential effects of social media on out-of-state and in-state donations may have important implications for the system of representation, political equality, and political polarization. In the United States, campaign contribution is an important medium through which political representation is expressed (Mansbridge 2003, Gimpel et al. 2008) and the basis of political representation is geographic. Thus, an increase in the relative importance of out-of-state donations might increase the discrepancy between *whom politicians represent* and *who supports them financially* and thus harm the integrity of the system of representation as well as political equality (Beitz 1989). An increase in the relative importance of out-of-state donations may also have implications for political polarization. People contribute to nonlocal candidates whom they sympathize with ideologically (Gimpel et al. 2008); thus, ideologically distinctive members are more likely to receive out-of-state

contributions.¹⁰ Thus, if out-of-state donations become relatively more important with the new information technology, then candidates with extreme ideological positions would have a higher chance of winning elections, which may increase polarization.

4.2. DATA

4.2.1. SOCIAL MEDIA ACTIVITIES

This study uses observations of social media activities by members of the 112th U.S. House of Representatives. The sample contains information about 416 politicians whose campaign finance data were identified, including 316 who have adopted Twitter. Out of the 316 Twitter accounts, I exclude accounts that are either inactive or premature,¹¹ and consider only the remaining 189 accounts as valid. I collected data on politicians' Twitter activities between June 8 and 22, 2011. These data include the exact date of their first Twitter posts, the number of followers, users followed, and the number of posts ("tweets") made at the time of data collection. I observed the politicians' number of Twitter followers once in June 2011. Even though I do not have observations on how the number of followers changed over time, I have observations on the dates when politicians adopted Twitter.

4.2.2. CAMPAIGN FINANCE

¹⁰ For formal theory that explains the relevance of political candidates' ideological profile in campaign donors, see, for example, Aldrich (1983), among many.

¹¹ I did not consider those politicians whose Twitter activities satisfy at least one of the following conditions: (1) the number of posts ("tweets") is smaller than 50; (2) it has been less than 6 months since they opened the account; or (3) the number of followers is smaller than 1000.

I obtained data on politicians' campaign finance from the Center for Responsive Politics.¹² The original source of these data was the publicly available Federal Election Commission (FEC) files on individual contributions between January 2005 and December 2010. The FEC maintains information on individual contributors who have donated more than \$200¹³ to a single politician, and previous evidence suggests that individual contributions in amounts of less than \$200 generally account for a very small part of the candidate's total fundraising (Gimpel et al. 2008).¹⁴ Because I am interested in the impact of politicians' social media network on their fundraising, I focus on individual contributions and exclude the contributions from political action committees (PACs) and self-financing.¹⁵ The data from the FEC contained information about the donations the representatives collected before they were elected. In order to control for the effect of incumbent status on donations, I excluded the donations that politicians had collected before they assumed their posts as representatives.¹⁶

4.2.3. IDEOLOGICAL EXTREMISM

I measure politicians' ideological extremism by the folded DW-Nominate score as in

¹² www.opensecrets.org

¹³ All money amounts are assumed to be in U.S. dollars. Candidates must disclose the names, addresses, and employers of any contributor who gives more than \$200.

¹⁴ According to the Center for Responsive Politics, large individual contributions (individual contributions greater than \$200) consisted of 47 and 48 percent of total contributions collected by House Democrats and Republicans, respectively.

¹⁵ In fact, individual contribution is a far more important source for political campaigns than contributions from political action committees (PACs) or corporations (Ansolabehere, deFigueiredo, and Snyder 2003; Thielmann and Wilhite 1989).

¹⁶ Alternatively, I included an indicator variable called $incumbent_{it}$, which takes a value of 1 if the politician collected donations when he or she was the representative and 0 otherwise. The estimated results were highly robust and do not depend on the specification.

previous studies (e.g., Chapter 1, Gimpel et al. 2008). Specifically, I first subtracted the median value from the DW-Nominate score and took its absolute value so that a value of 0 indicates a moderate ideological position with a median DW-Nominate score, and a positive number implies greater political extremism (either conservative or liberal). The DW-Nominate score and thus the extreme index was available for 334 politicians. Specifically, politician i 's extreme index is as follows:

$$extreme_i = |DW\ Nominate_i - median(DW\ Nominate_i)|$$

4.2.4. ADDITION DATA

I collected the following additional sets of data.¹⁷ In order to control for the geographical heterogeneity of online networks, I also collected information about followers' posted geographical information at the U.S. state level. When I excluded the number of Twitter users residing in foreign countries, approximately 85 percent of those who were following the politicians indicated their home state in the sample. I omitted those users whose geographic information was not available. In addition, in order to control for politicians' use of other social media tools such as Facebook, MySpace, YouTube, and RSS, I use an indicator variable to control for each social media tool. I also include an indicator variable for whether a politician chairs a committee. Table 4.5 describes these politicians' characteristics as variables included in the study.

¹⁷ I use these additional sets of data in the robustness check with cross-sectional observations. In panel data regressions, I use the politicians' fixed effect instead of controlling for the variables of politicians' characteristics.

Table 4.5: Politicians' use of social media other than Twitter

Variable	Politicians' Social media adoptions (%)	Standard Deviation
Facebook	65%	0.48
Flickr	19%	0.40
YouTube	75%	0.43
RSS	57%	0.50
MySpace	3%	0.18

4.3. THE IMPACT OF SOCIAL MEDIA ADOPTION ON FUNDRAISING

In this section, I investigate the impact of politicians' use of social media on their campaign finance. I am especially interested in whether (1) politicians saw an increase in their donations following their social media adoptions, (2) the political use of social media has made political finance more egalitarian, and (3) politicians with ideologically extreme positions have benefited most.

4.3.1. DOES SOCIAL MEDIA MATTER IN POLITICS?

By observing the dates that politicians adopted Twitter, I tested whether the donations to politicians increased *after* their social media adoptions, controlling for the characteristics of the politicians and contributors as well as for common time trends in the donations to all representatives combined.

Given that I have weak priors on the functional form of how donations will change after politicians adopt Twitter, I start by estimating a generalized additive

model (GAM) rather than by estimating an ordinary least squares (OLS) regression, which must specify a functional form in advance. GAM is a semi-parametric technique, which allows the relationship between the explanatory and outcome variables to take a flexible, smooth functional form (Jackman and Beck 1998). The empirical framework I use in this section is as follows:

$$\begin{aligned}
 Donations_{ijt} = & \alpha_0 + \mathfrak{G}(adopt_{it}) + outofstate_{ij} + f(t) \\
 & + timetoelection_{it} + \alpha_j + \alpha_i + \epsilon_{ijt}
 \end{aligned} \tag{5}$$

The dependent variable $Donations_{ijt}$ is either the number of individual contributors or the amount from individual donations from state j to politician i at monthly time indicator t . I transformed this variable logarithmically to interpret coefficients as percentage changes. The variable $adopt_{it}$ measures the number of months passed after or remaining before politician i adopted Twitter. Thus, $adopt_{it}$ is 0 when politician i has adopted Twitter, and $outofstate_{ij}$ is a dummy variable indicating whether region j is out-of-state for politician i . I also included α_i and α_j , which are the politician and state fixed effects, in order to control for unobservable characteristics of politicians and contributors, respectively.

I control for $f(t)$, which is the general time trend of donations,¹⁸ as well as $timetoelection_{it}$, which is a set of dummy variables indicating the number of months remaining before politician i 's next election. By controlling for $timetoelection_{it}$, I could compare, for instance, the donation that each politician

¹⁸ Because of the limited capacity of the statistical package R in estimating GAM, I control for a quadratic time trend in equation (5), rather than for a nonparametric time trend. Yet, I control for a nonparametric time trend in OLS estimations.

collected one month before election in 2010 with what he or she had collected one month before election in 2006 or 2008.

The sample for GAM estimation includes only the 72-month window around politician i 's Twitter adoption. The 72-month treatment window begins 3 years (36 months) before the adoption of Twitter. The pre-adoption periods are included to verify whether the increase in donations after the adoption can be attributable to politicians' Twitter adoption.¹⁹

I estimated the regression in (5) with a full sample and then separately for donations from out-of-state and in-state²⁰ to determine whether the impact of Twitter adoption on donations differs between these two regions. Figures 4.1 and 4.2 show the estimated effects from equation (5), along with 95 percent confidence bands,²¹ for the full sample, including donations from both in-state and out-of-state. Figure 4.1 uses the number of donations as the dependent variable, whereas Figure 4.2 uses the amount from donations.

¹⁹ The function $\mathbb{G}(\cdot)$ is a smooth penalized spline function, and the model also assumes that within each 72-month window the error in any single month is assumed to be normally distributed and correlated with previous shocks only through the last periods. The model estimates are calculated with the *mgcv* package in the statistical package *R*.

²⁰ For the regression described above to yield consistent estimates, the critical assumption is that the treatment (Twitter adoption) in a period is independent of the idiosyncratic shocks to donations in that period. In other words, after controlling for time-invariant characteristics, such as politician and state characteristics that affect donations in each period, the treatment (i.e., a politician's Twitter adoption) must be random across politicians. This is a strong but plausible assumption. The main factor determining the timing of a politician's Twitter adoption was assumed to be exogenous to time-varying factors.

²¹ The confidence bands are based on standard errors that were corrected for heteroskedasticity across politicians and serial correlation among politicians.

Figure 4.1: Impact of Twitter adoption on the number of donations over time

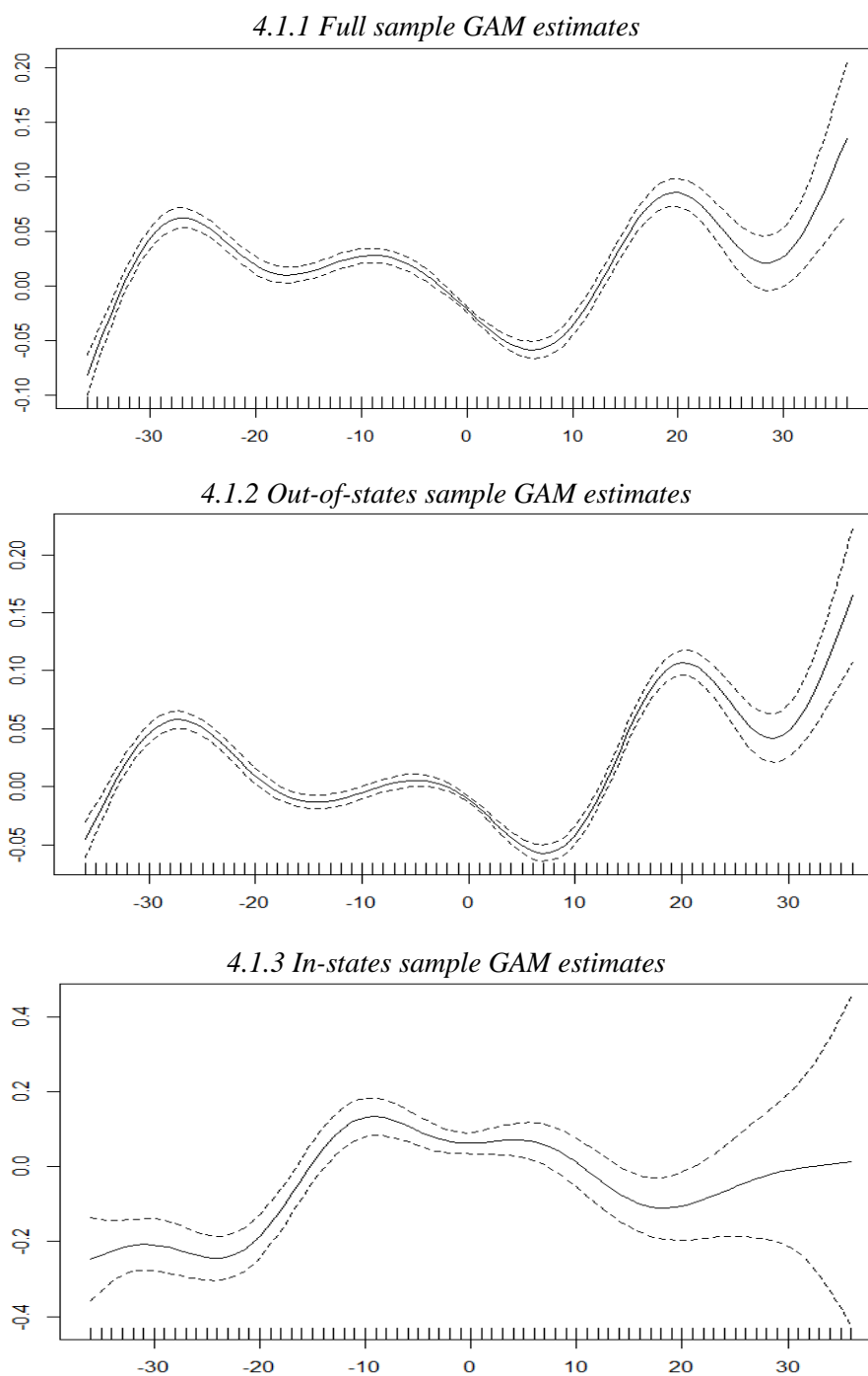
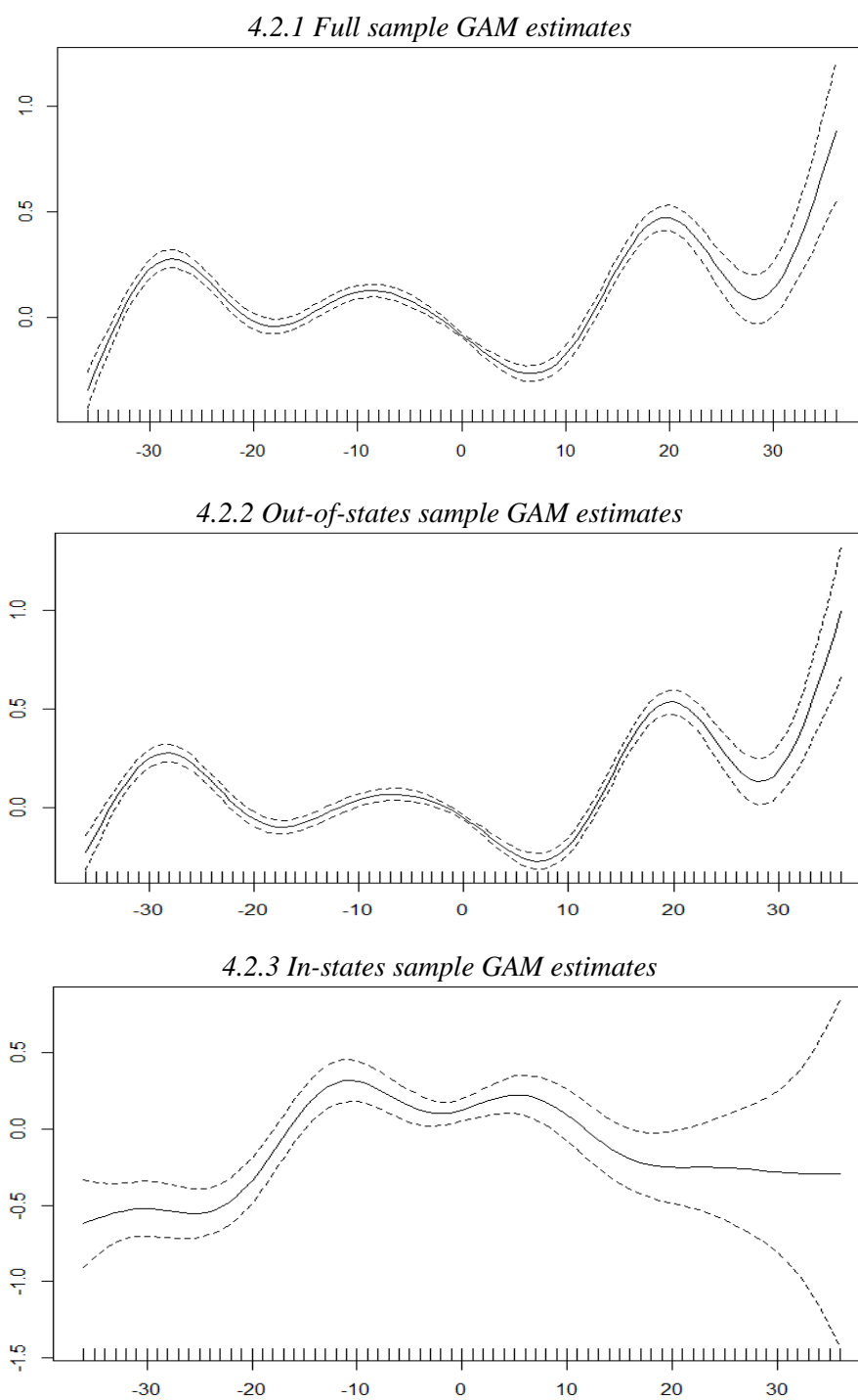


Figure 4.2: Impact of Twitter adoption on the amount of donations over time



Note: The horizontal axis is the variable $adopt_{it}$, which measures the number of months passed after or remaining before a politician i adopted Twitter. Thus, $adopt_{it}$ is 0 when the politician i adopted Twitter.

As can be seen in Figures 4.1 and 4.2, the estimated effects tend to become positive approximately 12 months after the adoption with an upward trend. As the dependent variable is the logarithm of donations, the estimated marginal impacts can be interpreted as approximate percentage changes in either the number of or amount from donations resulting from Twitter adoption. Thus, 36 months after Twitter adoption, politicians who adopted Twitter received approximately 15 and 90 percent more donations in terms of the number and amount, respectively, than those who did not. Another important point in Figures 4.1 and 4.2 is that in-state donations do not show the estimated effects on donations. The estimated coefficients tend to increase in the out-of-state sample (4.1.2 and 4.2.2), but not in the in-state sample (Figures 4.1.3 and 4.2.3).

4.3.2. DOES SOCIAL MEDIA CREATE A MORE EGALITARIAN POWER STRUCTURE?

A drawback of equation (5) is that the model does not consider the variation in the number of Twitter followers. Thus, the estimates in Figures 4.1 and 4.2 reflect the average impact for each time period after Twitter adoption. The problem, however, is that some politicians may have differentially benefited from using Twitter, depending on the size of their online networks. In order to address the question of *who* benefits from adopting the new technology, I first grouped politicians into 10 subgroups with respect to the size of their online networks (i.e., the number of Twitter followers) and ran the following regression:

$$\begin{aligned}
\text{Donations}_{ijt} = & \alpha_0 + \beta_1 \text{adopt}_{it} + \beta_2 \text{adopt}_{it} \text{followers}_i + \text{outofstate}_{ij} \\
& + f(t) + \text{timetoelection}_{it} + \alpha_j + \alpha_i + \epsilon_{ijt}
\end{aligned} \tag{6}$$

Now, adopt_{it} measures the number of months passed after politician i adopted Twitter. Thus, adopt_{it} is now an integer greater than or equal to zero. Unlike in equation (4), I assume that the impact of social media increases linearly after the adoption and estimate OLS instead of GAM because estimating an interaction impact with GAM is computationally too demanding.²² Politician i 's number of Twitter followers is followers_i , measured in ten thousands. I include the interaction between adopt_{it} and followers_i to see whether the effect estimated with equation (5) depends on the size of the networks on Twitter. The coefficient of this interaction term is expected to be positive, which can be a useful test to see whether the estimated effect with equation (5) is, in fact, associated with politicians' Twitter activities.

Tables 4.1 and 4.2 present the estimated results of equation (6). Again, I estimated the regression in (6) with a full sample and then separately for donations from out-of-state and in-state. For the full sample and out-of-state donations, the coefficient β_2 is estimated to be significantly positive. This evidence further supports that the estimated effects with equation (5) in Figures 4.1 and 4.2 are associated with politicians' Twitter activities. For in-state donations, however, the coefficient was significantly positive with the number of donations, but not with the amount. Overall, the associations between politicians' Twitter activities and donations are more

²² In fact, this linear assumption turns out to be a reasonable assumption from the semi-parametric GAM estimations in Figures 4.1 and 4.2.

obvious for out-of-state donations than for in-state donations.

Table 4.1: Impact of Twitter adoption on the number of donations
interaction with the number of Twitter followers

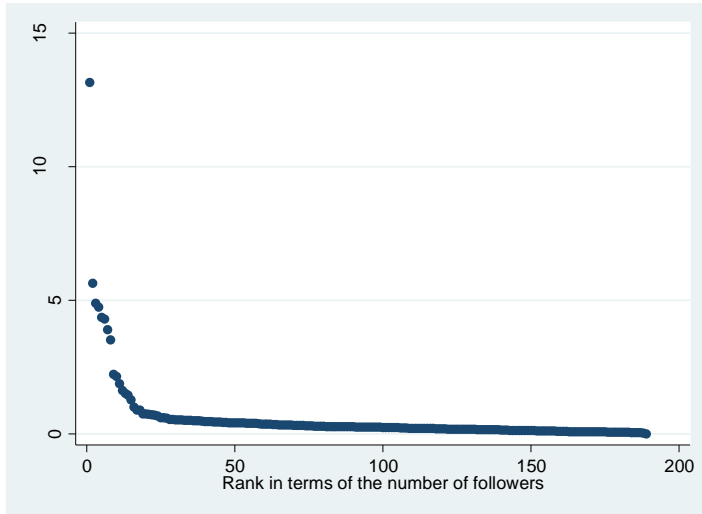
	(1)	(2)	(3)
	Full sample	Impacts on donations from out-of-states	Impacts on donations from in-states
Adopt	0.001* (0.000)	0.002** (0.000)	-0.008* (0.004)
adopt x followers	0.001** (0.000)	0.001** (0.000)	0.003** (0.001)
<i>N</i>	316,525	292,698	23,827
Adj. <i>R</i> ²	0.405	0.160	0.402

Table 4.2: Impact of Twitter adoption on the amount of donations
interaction with the number of Twitter followers

	(1)	(2)	(3)
	Full sample	Impacts on donations from out-of-states	Impacts on donations from in-states
adopt	0.007** (0.002)	0.009** (0.002)	-0.015 (0.010)
adopt x followers	0.005** (0.000)	0.005** (0.000)	0.003 (0.002)
<i>N</i>	316,525	292,698	23,827
Adj. <i>R</i> ²	0.271	0.147	0.370

1. Standard errors in parentheses: * $p < 0.05$, ** $p < 0.01$
2. The number of followers is in ten thousands

Figure 4.3: Highly concentrated number of Twitter followers



High-profile politicians' dominance on Twitter

Definition of high-profile politicians	Share of high-profile politicians' numbers of Twitter followers out of Representatives' total number of followers
Top 6	35.7%
Top 8	42.8%
Top 10	47.0%
Top 15	54.4%
Top 20	58.6%

The evidence that politicians with larger online networks have benefitted more than others suggests that political competition might become less egalitarian with the advent of information technology and its active use in politics. Figure 4.3 plots politicians’ number of Twitter followers as of June 2011 against their ranks in terms of the number. This figure shows that politicians’ Twitter networks are highly concentrated. The ten high-profile politicians having the largest number of Twitter followers possess almost half (47 percent) of all the representatives’ followers combined. In sum, the estimates imply that the active use of social media in politics may increase inter-candidate resource inequality in political competitions.

4.3.3. DO EXTREMISTS BENEFIT MORE FROM SOCIAL MEDIA?

As I show in Chapter 1, technology like the social media tends to more easily identify the more *salient* ideas (e.g., new ideas or ideas no one has ever talked about for some reason) and is thus more likely to benefit political extremists. Further, the evidence that donations have increased from out-of-state—albeit relatively little, if any, from in-state—leads us to consider the importance of ideology in the self-selection process. Out-of-state donors are more likely to be people who ideologically sympathize with politicians, so an increase in out-of-state donors may imply an increasing importance in ideology with reference to social media adoption.

$$\begin{aligned} \text{Donations}_{ijt} = & \alpha_0 + \beta_1 \text{adopt}_{it} + \beta_2 \text{adopt}_{it} \text{extreme}_i + \text{outofstate}_{ij} \quad (7) \\ & + f(t) + \alpha_j + \alpha_i + \epsilon_{ijt} \end{aligned}$$

Equation (7) aims to test this argument. I followed previous studies (e.g., Gimpel et al. 2008) in measuring ideological extremism. The variable extreme_i is the folded DW-Nominate score, which measures the ideological position of politician i , with a greater number referring to a more politically extreme position, either liberally or conservatively.

Table 4.3: Impact of Twitter adoption on the number of donations
interaction with ideological extremism

	(1)	(2)	(3)
	Full sample	Impacts on donations from out-of-states	Impacts on donations from in-states
adopt	0.002** (0.001)	0.002** (0.001)	0.005 (0.004)
adopt x extreme	0.002** (0.001)	0.004** (0.001)	-0.008 (0.005)
<i>N</i>	282,900	261,562	21,338
Adj. <i>R</i> ²	0.399	0.144	0.539

Table 4.4: Impact of Twitter adoption on the amount of donations
interaction with ideological extremism

	(1)	(2)	(3)
	Full sample	Impacts on donations from out-of-states	Impacts on donations from in-states
adopt	0.013** (0.003)	0.013** (0.003)	0.002 (0.010)
adopt x extreme	0.004 (0.003)	0.008* (0.004)	-0.021 (0.012)
<i>N</i>	282,900	264,008	21,338
Adj. <i>R</i> ²	0.262	0.128	0.357

1. Standard errors in parentheses: * $p < 0.05$, ** $p < 0.01$

2. The number of observations is smaller than in Tables 4.1-2 as DW Nominat scores were not available for all the politicians in the sample

Tables 4.3 and 4.4 report the estimated impact in terms of the number of and amount from donations, respectively. Overall, the results suggest that a large part of the financial benefits associated with social media adoption is observed among high-

profile politicians with ideologically extreme positions.²³ This evidence supports the argument that an increase in out-of-state donations may imply that political ideology is becoming increasingly important, with the recent emergence of social media as a political communication tool, in shaping the relationships between politicians and their donors.

4.4. ROBUSTNESS CHECK

My findings so far can be summarized as follows: (1) Politicians' Twitter adoptions have had a significantly positive effect on an increase in their out-of-state donations. (2) The effect was driven mainly by a small number of politicians with large online networks ("Twitter followers"). (3) The effect is higher for politicians with extreme ideological positions.

In this section, I focus on the first finding—the significant effect of social media adoption on fundraising—and present two additional tests that support the estimated result. First, I estimate a model with cross-sectional observations to determine whether the estimated result appears consistent with the previous finding. In the previous section, the empirical strategy was to test whether donations increased *after* politicians adopted Twitter. However, this time-series observation is missing an important part of the story by overlooking the association between a politician's number of Twitter followers from state j and the politician's donations from state j . If Twitter adoptions have an impact on donations, it would be reasonable to find a

²³ In fact, the estimated effect was not symmetric for left- and right-leaning politicians. Republican extremists have enjoyed a much larger extremism premium than Democrat extremists have.

positive association between these two variables. This association can be tested in only cross-sectional observations as the number of followers was observed once in June 2011. Thus, I examine whether an increase in politician i 's Twitter followers from state j is associated with an increase in politician i 's donations from state j .

The second robustness check involves focusing on the politicians with the highest number of Twitter followers to determine whether their donations have increased. Given the evidence so far, it is reasonable to expect that those high-profile politicians would have had a higher increase in donations than a comparable group of politicians. I restrict my attention to the six topmost politicians, who are those with more than 40,000 followers as of June 2011, and employ a difference-in-difference (DID) strategy to see whether their financial benefits have been greater than those of other politicians from the same states.

4.4.1. CROSS-SECTIONAL OBSERVATIONS

The following model forms the basis of the empirical analysis in this section. Suppose that before social media was actively used in politics, donations from state j to politician i were determined by three factors: politician i 's individual characteristics, state j 's characteristics, and whether state j is out-of-state for politician i . Subsequently, after politicians began to use social media to communicate with their potential supporters, the donations are also affected by the politicians' use of new information technology ($Followers_{ij}$ and $OtherSocial_i$).

$$\begin{aligned}
Donations_{ij}^A &= \alpha + \beta Followers_{ij} + \delta OtherSocial_i & (8) \\
&+ outofstate_{ij} + \alpha_j + \alpha_i + \varepsilon_{ij}
\end{aligned}$$

$$Donations_{ij}^B = \alpha + outofstate_{ij} + \alpha_j + \alpha_i + \varepsilon_{ij} \quad (9)$$

$Donations_{ij}^A$ and $Donations_{ij}^B$ are measures of fundraising from region j to politician i . I use either the number of or the total amount from donations for $Donations_{ij}^A$ and $Donations_{ij}^B$. Superscripts A and B indicate the periods before and after the introduction of social media. $Donations_{ij}^B$ is the donations during the 2005-2006 election cycle, while $Donations_{ij}^A$ is the donations during the 2009-2010 election cycle. Thus, for these cross-sectional observations, I limit my sample to the politicians who worked as representatives in both cycles. The state and politicians' fixed effects are α_j and α_i , respectively, and $outofstate_{ij}$ is a dummy variable indicating whether region j is out-of-state for politician i . $Followers_{ij}$ is the number of politician i 's Twitter followers from region j , and $OtherSocial_i$ is the set of covariates that measure politician i 's adoption of social media technology other than Twitter. These include Facebook, MySpace, YouTube, and RSS (see Table 4.5 for additional information). I also include a dummy variable indicating whether politician i newly became the chair of a committee during 2009-2010.

Then, I subtracted equation (9) from equation (8) to arrive at equation (10), the estimated functional form. Note that the politician and state fixed effects are removed in this equation. Both $Followers_{ij}$ and $Donations_{ij}^{A\ or\ B}$ are transformed logarithmically in order to interpret coefficients as percentage differences. The

dependent variable $\Delta Donations_{ij}$ is the change in the log number of or amount from politician i 's individual donations from region j .

$$\Delta Donations_{ij} = \alpha + \beta Followers_{ij} + \delta OtherSocial_i + \varepsilon_{ij} \quad (10)$$

As in previous sections, I estimate equation (10) separately for in-state and out-of-state donations. Table 4.6 presents the estimated results of equation (10). Although the fit of the model was poor, as indicated by the R-squared statistics, the result still supports the previous estimates that politicians' Twitter adoptions had a positive impact on out-of-state donations. A 100 percent increase in the number of Twitter followers from a state was positively associated with a 16 percent change in the number of individual contributors and an 8 percent change in the amount from individual donations from that state. These estimates support the finding in the previous section.

Table 4.6: Estimated association between Twitter followers and donations

Dependent variable : $\Delta Donations_{ij}$	(1)	(2)		(3)	(4)	(5)		(6)
	Full sample	The number of donations		Impacts on donations from in-states	Full sample	The amount of donations		Impacts on donations from in-states
		Impacts on donations from out-of-states	Impacts on donations from in-states			Impacts on donations from out-of-states	Impacts on donations from in-states	
$Followers_{ij}$	0.141** (0.009)	0.162** (0.010)	-0.056 (0.044)	0.024 (0.039)	0.075* (0.045)	-0.355 (0.241)		
N	4,952	4,759	193	4,952	4,759	193		
Adj. R^2	0.080	0.088	0.041	0.008	0.009	0.136		

Note: 1. Standard errors in parentheses: * $p < 0.10$, ** $p < 0.05$

4.4.2. IS THE BENEFIT OBSERVABLE AMONG TOP POLITICIANS?

Here, I focus on six politicians whose number of Twitter followers was greater than 40,000 as of June 2011.²⁴ Hereafter, I call those six the “top politicians,” whom I regard as the treatment group. The control group is the group of politicians who are representatives from the same states as each of the top politicians. The six members come from Ohio, California, Wisconsin, Arizona, Minnesota, and New York, so the other representatives from each of those states form the control groups.

In order to employ a DID, I define before- and after-treatment as follows. In the previous section, I showed that the effect of Twitter adoptions is positively associated with the size of online networks (number of “Twitter followers”). Given the evidence that the size of online networks is highly concentrated, I assume that only the six politicians have financially benefited from Twitter adoption; thus, I define the after-treatment period as the period after the top six politicians adopted Twitter. Thus, the same cutoff applies for each state, but before- and after-treatment classifications may differ across states. Hence, the empirical strategy is to estimate the following equation.

$$Donations_{it} = \alpha + \beta TopPol_i + \gamma After_t + \delta TopPol_i After_t + \varepsilon_{it} \quad (11)$$

$TopPol_i$ is an indicator variable with a value of 1 if the politician is the top politician, and 0 otherwise. $After_t$ is a dummy variable indicating the period during which the

²⁴ Those six are John A. Boehner, Nancy Pelosi, Paul Ryan, Gabrielle Giffords, Michele Bachmann, and Anthony D. Weiner. The threshold of 40,000 is somewhat arbitrary, but the estimated result in this section is robust with different thresholds.

top politician adopted Twitter. The DID estimate, which is of particular interest, is δ , which captures the financial benefits the top politicians have received from their Twitter adoption. The sample covers the period between January 2005 and June 2011.

The estimated result is reported in Table 4.7. The result indicates that the top politicians had a 130 percent increase in out-of-state donations, in either number or amount, after they adopted Twitter compared to other politicians from the same state. This financial benefit was not clearly observed among in-state donations. We can once again verify this estimate in Table 4.8 and Figure 4.5, which report, respectively, the percent changes in donations for all the groups included in the DID estimates and the time-series change in the amount from out-of-state donations for the six politicians. Figure 4.5 shows that the top politicians, except for Nancy Pelosi, have had an increase in out-of-states donations following their Twitter adoptions.

Table 4.7: Difference-in-Difference Estimates of Top politicians versus Others

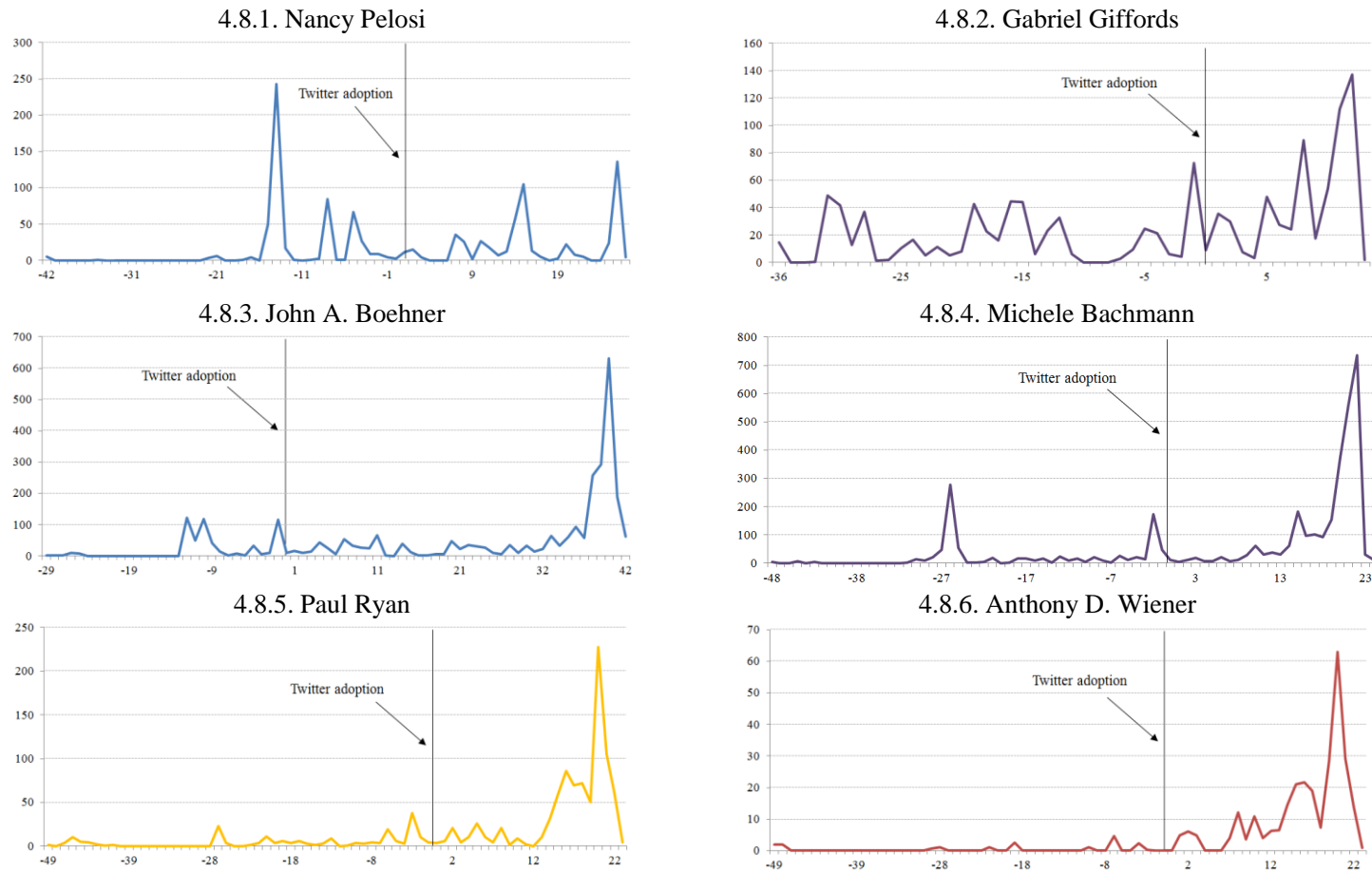
	(1)	(2)	(3)	(4)	(5)	(6)
	The amount of donations			The number of donations		
	Full sample	Impacts on donations from out-of-states	Impacts on donations from in-states	Full sample	Impacts on donations from out-of-states	Impacts on donations from in-states
$TopPol_i$	0.691** (0.300)	0.611 (0.440)	0.771** (0.245)	0.537* (0.308)	0.494 (0.414)	0.579* (0.316)
$After_t$	-0.116 (0.252)	-0.141 (0.251)	-0.0917 (0.305)	-0.0404 (0.233)	-0.0703 (0.223)	-0.0104 (0.218)
$TopPol_iAfter_t$	0.816* (0.426)	1.353** (0.644)	0.279 (0.418)	0.756 (0.473)	1.277* (0.709)	0.236 (0.509)
N	48	24	24	48	24	24
adj. R^2	0.383	0.467	0.418	0.261	0.361	0.176

Note: 1. Standard errors in parentheses: * $p < 0.10$, ** $p < 0.05$

Table 4.8: Percents change in donations: Top politicians versus Others

Treatment versus Control Groups	In-states donations		Out-of-state donations	
	% change in		% change in	
	the amount of donations	the number of donations	the amount of donations	the number of donations
Other Representatives from AZ (Average)	-62%	-46%	-63%	-43%
Gabrielle Giffords	-38%	-24%	37%	34%
Other Representatives from CA (Average)	15%	14%	15%	8%
Nancy Pelosi	-16%	-11%	1%	15%
Other Representatives from MN (Average)	43%	30%	-4%	-12%
Michele Bachmann	21%	46%	454%	613%
Other Representatives from NY (Average)	-43%	-35%	-47%	-47%
Anthony D. Wiener	17%	1%	369%	183%
Other Representatives from OH (Average)	127%	166%	133%	178%
John A. Boehner	331%	304%	826%	756%
Other Representatives from WI (Average)	-28%	-33%	-15%	-19%
Paul Ryan	-3%	-5%	336%	434%

Figure 4.5: Time trend of out-of-state donations (in thousands USD) of the top six politicians in terms of the number of Twitter followers



Note: The horizontal axis is the variable $adopt_{it}$, which measures the number of months passed after or remaining before a politician i adopted Twitter. The horizontal axis covers a 6-year period from January 2005 to December 2010.

4.5. FINDINGS & POLITICAL IMPLICATIONS

This study presents evidence that (1) politicians' social media adoptions have yielded increased donations from outside their constituencies but little from their own constituencies, (2) politicians with extreme ideologies tend to benefit more from their social media adoptions, and (3) the political use of social media may yield increased inter-candidate resource inequality.

The first and second findings have important implications for the integrity of the system of political representation as well as for political polarization. They suggest that politicians' use of new information technologies neutralizes the importance of geographical distance and highlights ideological positions, therefore increasing the discrepancies between *whom they represent* and *who supports them*. This phenomenon may be detrimental to the integrity of the system of representation, as it calls into question politicians' incentives in representing their constituents. “[W]hen financial incentives encourage legislators to subordinate the interests of their constituents to those of others elsewhere, an additional form of distortion in the system of representation is introduced” (Beitz, 1989, 204).

Further, the two findings may imply an increasing political polarization due to the use of social media. The Internet may bring *new people* into political giving but may not bring in *new kinds of people* (Schlozman et al. 2008). However, even if the Internet does not significantly change the profile of donors in the U.S. as a whole, the political implications may change with an analysis from the standpoint of each politician. That is, new technologies like social media allow politicians to communicate with a “self-selected” group of people online who may have different

profiles from those whom the politicians used to ask for support offline. One possibility is that the “self-selection” technology reduces the information barriers between individuals and nonlocal politicians, and allows politicians more easily to communicate with people who are from remote geographical locations but who sympathize with them ideologically. That is, all else being equal, out-of-state donors are more likely to be those who sympathize with the politician ideologically (Gimpel et al. 2008), and the evidence of the increased out-of-state donations as well as greater financial benefits for political extremists may contribute to the greater ability of ideologically intense or extreme candidates to win elections, thereby increasing political polarization.²⁵

The third finding also has an important implication for political equality, which is a fundamental premise of democracy (Verba et al. 1995, Dahl 2006). To begin with, the “surrogate representation” in the United States is often criticized as “embodying far more political inequality than does even the traditional legislator-constituent relation” (Mansbridge 2003, 523) because the representation is often exercised through monetary contributions. Thus, it is often argued that in order to secure political equality, the system of political finance in the United States should ensure that politicians who participate in political competition have equal opportunities for effective political influence (Dahl 1989, Beitz 1989, Cohen 2001).²⁶ Although there is no consensus as to whether equality of resources is necessary for political equality (Beitz, 1989, Wright, 1987, Cohen 2001), equality of resources still may serve “as a

²⁵ Previous studies report that political extremists are more successful in terms of fundraising (see, for example, Ensley 2009; Gimpel et al. 2008) and that this advantage may increase even further with the widespread use of the “self-selection” technology.

²⁶ See also John Rawls, *A Theory of Justice*, p. 63, for similar arguments.

convenient proxy for a more complex criterion that would be excessively difficult to interpret and administer” (Beitz 1989: 209). Thus, evidence that the widespread political use of social media results in increased inter-candidate resource inequality implies that the use of new information technology may aggravate rather than alleviate political inequality.

4.6. LIMITATION & CONCLUSION

This study examined whether politicians’ social media adoptions have influenced their fundraising. My findings suggest that donations significantly increased after politicians adopted social media. Notably, such adoptions have a more dramatic impact on out-of-state donations, as there was little evidence that donations from politicians’ own constituencies increased following social media adoption.

My findings have important implications for the integrity of the system of political representation, political polarization, and political equality. They also shed light on the recent debate about the impact of new information technology on democracy. The estimated impact of the new information technology on fundraising was much greater than I had anticipated. However, because this study has analyzed a phenomenon that continues to evolve rapidly, this estimated impact can hardly be regarded as representing the full and final impact of the new social media (Schlozman et al., 2010; Bimber, 1998; Xenos and Moy, 2007). Similarly, although I observed financial benefits only among politicians with large online networks, as other politicians’ online networks grow and mature, the unequal benefits across politicians may become less concerning.

Further, although the overall pattern of my findings reflects the effect of politicians' social media adoptions, more work would be needed to obtain a more precise estimate of causality. For instance, the effect I tested with politicians' Twitter adoptions might need to be understood as the effect of politicians' social media adoptions. If these politicians adopted other social media technologies at the same time they adopted Twitter (a highly likely possibility), the effects may be overestimated, and we should attribute the estimated effect to political use of the new social media in general, rather than to Twitter in particular. Nevertheless, this study is among the first to demonstrate empirically the impact of social media adoptions on political finance and discuss its implications for political equality, polarization, and democracy.

In Chapter 1, I empirically showed that online institutions like the social media concentrate and polarize people's information consumption patterns, and may thereby concentrate and polarize people's political behaviors (e.g., political giving) as well as political outcomes (e.g., political finance), all of which are important political implications. Considering the evidence that a significant part of the observed concentration and polarization is attributable to cascading (Chapter 1), my findings challenge the notion that Internet-mediated political actions or communications will necessarily promote democracy.

4.7. APPENDIX

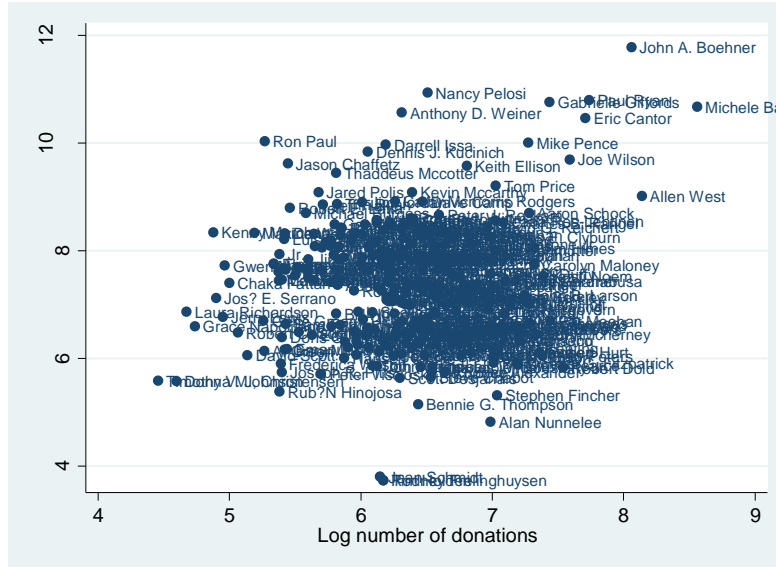
DESCRIPTIVE COMPARISON OF ONLINE AND OFFLINE NETWORKS

Here, I attempt to compare politicians' networks on Twitter with their "offline" networks in terms of the sizes and geographical diversity of the two networks. The problem that arises in such a comparison is that politicians' networks, especially those offline, are hardly observable. In this study, I use the online information obtained from the politicians' social media sites for their online networks and information about individual contributors as a proxy for their offline networks.

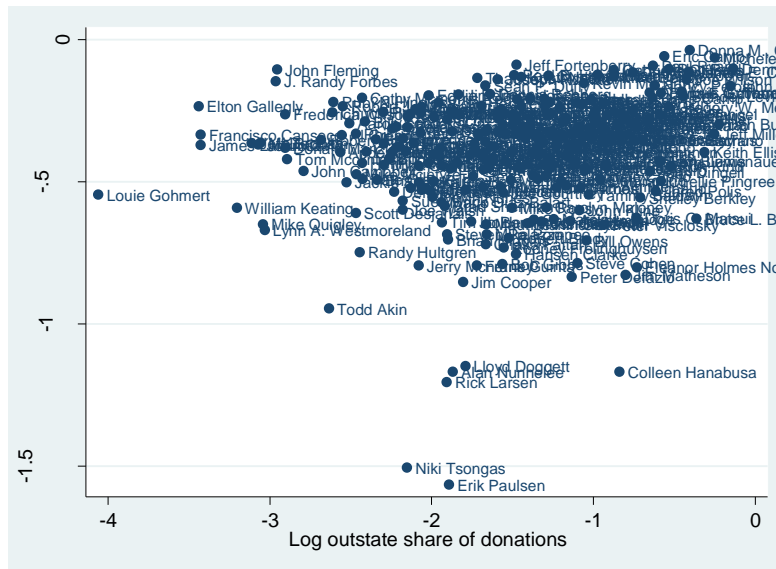
One obvious limitation in comparing online and offline networks is that Twitter followers are not directly comparable to individual contributors. To become a Twitter follower, one needs only to click on the politician's Twitter webpage, which requires a much lower level of dedication compared to that of someone who donates more than \$200 to the politician's campaign. Nevertheless, the results of the comparisons provide a motivation for the analysis presented in the previous sections. Findings suggest that the distribution of online networks (Twitter followers) is significantly different from that of offline networks (individual contributors): the former is more concentrated and geographically diverse. These differences may be attributable to the different levels of commitment required by the two networks, but social media may also allow politicians to build networks online that are qualitatively different from those built in more traditional ways.

Figure 4.7 : Scatter plots: Online vs. Offline networks

4.2.1. Network sizes: online vs. offline



4.2.2. Out-of-state shares: online vs. offline networks



Data source : twitter.com; friendorfollow.com; Center for Responsive Politic

4.7.1. CONCENTRATION

It is not clear whether politicians' online networks in Twitter are also as highly concentrated as online traffic. Unlike online traffic to newspaper sites, "following" is an expression of explicit interest; therefore, it is less susceptible to cascading, in which online traffic becomes concentrated through search engines and aggregator sites (Hong 2012). Furthermore, I would expect relatively less traffic to be directed to politicians' Twitter accounts by search engines or aggregators, as people often search for politicians' names to find their Twitter accounts. Thus, the question of whether politicians' online networks in Twitter are concentrated is a matter for empirical investigation.

I conducted two descriptive analyses in order to compare the sizes of online and offline networks. First, I plotted Lorenz curves for both online and offline networks and then conducted the Kolmogorov-Smirnov (K-S) test to compare the network distributions. Table 4.9 presents the results of the K-S test, indicating a statistically significant difference between the two distributions. Figure 4.6 plots the Lorenz curves²⁷ for the online and offline networks. Taken together, the K-S test and Lorenz curves show that the distributions of online and offline networks differ, the online network being more concentrated.

²⁷ A Lorenz curve is a graphic representation of the cumulative distribution function of the empirical-probability distribution. Every point on the curve represents a statement such as, "The bottom x percent of all politicians have y percent of the total market share." Thus, Figure 1 shows that the top 10 percent of politicians own approximately 22 percent of the total offline market share. For the online market share, however, the top 10 percent owns 55 percent of the market.

Figure 4.6 : Lorenz Curves of Online and Offline Networks

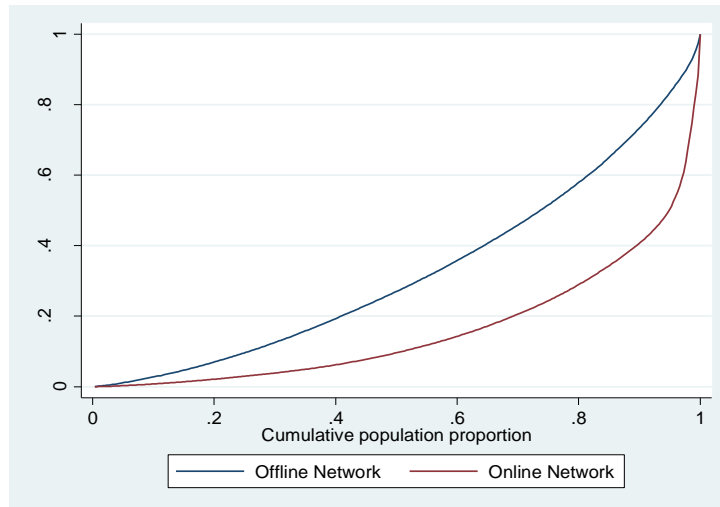


Table 4.9: Two-sample Kolmogorov-Smirnov tests for Equality of the Two

Distributions

Smaller Group	Coefficient D	P-value	Corrected
Offline network	0.7441	0.000	
Online network	0.0000	1.000	
Combined Kolmogorov-Smirnov Test	0.7441	0.000	0.000

4.7.2. GEOGRAPHICAL DIVERSITY

The social media foster communication among a more diverse group of people and allow politicians to connect with people who are geographically distant but who share a common interest in policy issues. To test the geographical diversity of online and offline networks, I defined the two variables outlined in the foregoing chapter: *out-of-state* and *in-state shares*. When comparing geographic information between offline and online networks, I excluded international Twitter followers from the total number

of followers, considering only those within the U.S.

As in the previous analysis of network size, I compared Lorenz curves for the offline and online out-of-state shares and conducted a K-S test. Both tests indicated that the distributions of offline and online out-of-state shares differed, with the online network being more geographically diverse.

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