Impact of Market Structure on Regulatory Compliance: Evidence from Online Censorship in China

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Abstract

This paper studies the role of market structure in regulatory compliance through a unique empirical example: censorship via content removal by three major live-streaming platforms in China. Adopting an event study approach, this paper exploits the unexpected occurrence of 30 salient events over two years and shows that platforms of different sizes censor a different number of keywords with notably different delays. This paper then develops a structural model where the platform's profit depends on its own censorship action as well as that of its competitors, induced by the switching behavior of users with heterogeneous preferences for censorship. By complying with the government's censorship request, platforms may lose users who prefer to evade censorship by switching out. By not complying, platforms incur a cost imposed by the government that is positively correlated with their sizes, but it also allows them to attract new users from their competitors that are obedient. The model predicts that while large platforms censor more often than their small competitors due to higher political cost, centralizing market power via merging or shutting down small platforms not necessarily generates more censorship in the marketplace.

Keywords : Censorship, strategic interaction, market concentration, event study

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1 Introduction

In many industries, firms act as the intermediary to implement government regulations. For instance, private firms collect sales tax (Anderson et al., 2010), manufacturers recall products of harm (Chao et al., 2009), and digital platforms remove contents upon request by the government. In the case of content removal, regulations take many forms: resolving copyright infringement, removing content that violates the privacy of an individual, and in some cases, media censorship. While media censorship is not a common practice in the West, global lawmakers push for stricter regulations on social media platforms following data breach scandals and terrorist groups using social media as a recruiting device (Arnold, 2018). Much debate centers around the legitimacy of regulating social media (Nooren et al., 2018), but the effectiveness of such regulations attracts less attention. For example, in 2017, Germany's parliament passed a law forcing social networks to delete hate-speech postings and misinformation within 24 hours, or they would face fines of up to €50 million (Oltermann, 2018). However, firms have not always complied with those regulations in a prompt manner. The Ministry of Justice in Germany criticized Facebook for not promptly handling user complaints, saying that the company deleted only 39% of the criminal content reported by users. Twitter's compliance was not found satisfactory either: a German government-funded survey found that Twitter erased only one of a hundred user messages that violated the regulation, and none of the deletions took place within 24 hours (Lomas, 2017). If the implementation of a regulation places a firm at a competitive disadvantage while benefits others in providing products or services, the firm may have an incentive to circumvent this regulation. How does competition affect such incentives of a firm, and consequently the market-level compliance?

This paper studies these questions through a unique example: censorship via content removal by online platforms in China. Using a novel dataset on three major live-streaming platforms, I measured each platform's compliance behavior by examining when and how many keywords the platform has added to its own blacklist following a sequence of salient events. The dataset contains the complete history of blacklisted keywords adopted by each of the three platforms over two years (2015-2017). If a user's message contains any blacklisted keyword in a chat on the platform, his/her message will either be undelivered or replaced by asterisks. I exploited the unexpected occurrence of 30 political and social events during the data collection period, such as the 2015 Tianjin Explosion that killed nearly 200 people and fueled fear of toxic air and distrust of government, and the 2016 international tribunal that ruled against China's claim to the historic rights of the South China Sea area. Those salient events triggered Chinese government's censorship request and surveillance, as well as the need for platforms to comply. By comparing the timing and frequency of platforms' blacklists update with an event study approach, I find that platforms of different sizes exhibit different compliance behavior: the largest platform not only censored a higher number of keywords on average, it also complied faster than the smaller platforms.

Motivated by the event study results, this paper develops a structural model of oligopolistic competition to investigate the relationship between platforms' size, political pressure, and their compliance with censorship regulations. In this model, a platform's profit depends on its own censorship action as well as that of its competitors, induced by the switching behavior of users who have heterogeneous preferences for censorship. In the arrival of an unexpected event, digital platforms receive requests for censoring a set of keywords related to these events and decide simultaneously whether to comply immediately or not. Users obtain disutility from being censored and may evade censorship by switching to another platform which incurs a fixed switching cost. If the switching users find out that the new platform also censors their messages, they will leave the new platform immediately for outside options such as watching TV or listening to music. On the one hand, platforms are under legal pressure to remove certain user-generated content immediately. If they fail to do so, platforms are subject to a fine and may risk being temporarily shut down by the government (King et al., 2013). On the other hand, by strategically delaying censorship, a platform may attract users who try to evade censorship by switching between platforms. The model predicts that while large platforms censor more often than their small competitors due to higher political cost, centralizing market power via merging or shutting down small platforms not necessarily creates more disruption in users' content creation.

If a market hosts *fewer* platforms, two factors are at play: first, each platform captures a larger market share and bears higher political costs of non-compliance; second, platforms have more strategic incentives to differentiate from other obedient competitors by not complying immediately, now that users have fewer options to switch to. Following this change in the market structure, whether a platform is more or less likely to censor during the next salient event depends on which of the two forces dominates. If even a slight increase in a platform's size alarms the government and significantly raises its risk of non-compliance, the former political pressure would dominate and generate more censorship in the marketplace. If, on the other hand, limiting the number of alternatives significantly increases a platform's chance to capture more switching users, then the latter strategic incentive would dominate and cause platforms to censor less often in equilibrium. To quantify the relative magnitude of these two forces and derive meaningful counterfactual predictions, I estimated the model by exploiting variations in platforms' market share across different events in my dataset. My counterfactual analysis shows that permanently shutting down a small platform could backfire and lead to an unintended consequence where the overall censorship is lower in the marketplace.

Past research (Edmond, 2013) suggested that an authoritarian regime's chances of survival decline with the number of information sources unless there are strong economies of scale in information control. For this very reason, authoritarian regimes such as China and Russian have always been heavy-handed in regulating private media outlets to preserve political power. With nearly half of the total world population owning a social media account (Newberry, 2019), however, blindly penalizing emerging platforms for non-compliance no longer comes with a negligible cost in this digital age. My findings suggest that decentralizing online market power may help an authoritarian government maintain sufficiently high market-level of censorship in an overall low-pressure environment: tolerating a bit of dissent on small platforms allows large platforms to censor more effectively as it mitigates their strategic incentives. This might be one of the reasons why, unlike the US market which is dominated by a handful of mainstream social media platforms, Chinese social media is still "very fragmented and localized" (Chiu et al., 2012).

Beyond authoritarian regimes, this paper also offers some useful insights on regulating digital platforms in Western democracies. Although most people dislike misinformation and wish it removed, a piece of "fake news" takes time to verify and it sometimes becomes the "alternative truth" among many before it is proven deceptive. In fact, creating borderline content has become "one of the few proven recipes for success" as it brings more engagement "the closer a piece of content comes to violating a platform's rules" (Newton, 2019). When two segments of users co-exist: one is quick to identify misinformation and the other takes it as the alternative truth, removing the same piece of content pleases the former at the expense of upsetting the latter. If large platforms are expected to be "more responsible" for removing misinformation or to take actions faster, the latter group may disproportionally switch to small platforms that receive less legal attention every time a piece of misinformation turns viral. Subsequently, social media mergers and acquisitions not only affect the parties involved, but they could also significantly distort other small incumbents' incentives to comply with the regulation - a distortion that may exacerbate the spread of misinformation and create more "echo chambers" in the long run. To counter misinformation, policymakers should therefore pay extra attention to small platforms especially when large platforms are pressured to purge borderline contents quickly.

The rest of the paper is organized as follows. Section 2 discusses the related literature. Section 3 describes the data and institutional background. Section 4 presents the event-study analysis and results. Section 5 proposes the model and discusses a series of model predictions. Section 6 describes the estimation strategy and explores its finite sample performance through a Monte Carlo experiment. Section 7 presents the estimation results and draws counterfactual predictions. Section 8 concludes.

2 Literature Review

My research draws from both theoretical and empirical literature that lies at the crossroads of economics, marketing, and political science. An extensive marketing literature has explored the impact of competition on the advertising, product decisions, and market positions. For instance, Dukes (2004) models how certain market parameters affect the competitive level of advertising chosen in the market and Dukes (2006) examines how media concentration can affect the prices of advertised products. Gal-Or and Dukes (2003) show that competition for media audiences encourages restrained levels of informative advertising and consequently higher advertising and product prices. Empirically, Orhun et al. (2015) investigate the impact of entry and competitive incentives on product choices and revenues in a movie exhibition industry. Zhang and Sarvary (2011) model competition between social media sites, where they show that ex-ante identical sites can acquire differentiated market positions that spontaneously emerge from user-generated content. My work complements the above literature by empirically investigating how another dimension of the firm's strategy, i.e. its compliance with regulations, is affected by the competitive pressure.

Another important strand of literature closely related to this paper is on "media bias". It is popularized by Mullainathan and Shleifer (2002) who refer to it as "media's choice of positioning to pander to consumers' political taste." This phenomenon has been explored in many theoretical contexts. For example, Prat and Strömberg (2013) study the incentives which shape the political orientation of the news media. Gentzkow et al. (2014) reinforces the idea that the incentive to differentiate ideologically from competitors increases diversity significantly, offsetting a strong incentive to cater to the tastes of majority consumers. Yildirim et al. (2013) discuss the incentives of online newspapers in restricting user-generated content. In addition, several papers have empirically proposed different strategies to identify and measure media bias (Groseclose and Milyo, 2005; Gentzkow and Shapiro, 2010; Durante and Knight, 2012). Although this paper also studies firms' incentives in filtering selective information, it is different from the above-mentioned research by focusing on the timing, instead of the content, of censorship.

This paper also draws from and contributes to empirical work on the discrete choice models of firms' stra,tegic decisions. The identification and estimation of discrete games have been studied in several structural contexts (Bramoullé et al., 2009; De Paula and Tang, 2012; Bajari et al., 2006). For example, Sweeting (2004) shows that radio stations have stronger incentives to coordinate and air commercials at the same time during rush hours and in smaller markets. In a follow-up paper (Sweeting, 2009), he estimates the strategic incentives of radio stations through the lens of an incomplete information game. De Paula and Tang (2012) generalize the identification method proposed in Sweeting (2009) to a non-parametric context. Aradillas-Lopez and Gandhi (2013) develop a test conjecture on firms' strategic interactions that have an economic interest, such as whether players care equally about the decisions of each opponent or whether there is asymmetry in the effect of strategic interaction and how these effects vary with continuous market covariates. Methodologically, the paper most related to mine is Wan and Xu (2014), where they propose an inference procedure for a static binary decision game of incomplete information that allows for the correlation of private signals. Unlike Wan and Xu (2014), this paper develops a full structural model that micro-founds the strategic interaction between firms by modeling the demand-side behavior explicitly. This paper shows how the strategic interaction term in the "reduced-form" profit function can be mapped to a set of structural parameters with important economic implications in my framework.

Finally, this paper contributes to an extensive literature on censorship and media capture (e.g. King et al. (2013); Edmond (2013); Lorentzen (2014); Gehlbach and Sonin (2014); Qin et al. (2018); Qin et al. (2016); Hobbs and Roberts (2018)). Most existing papers either empirically examined the nature of censored content and how social media users responded to the act of censorhsip, or theoretically modeled an authoritarian government's political strategy to implement censorship policy. To the best of my knowledge, instead of focusing on the political value of censorship at a regime level, this paper is the first to study the economic incentives that influence censorship at the firm level as a result of competition.

3 Data and Institutional Background

Section 3.1 describes each dataset at length. Section 3.2 introduces the institutional background of censorship in China. Section 3.3 provides an overview of the social media platforms studied in this paper.

3.1 Data

The primary source of data is provided by the Citizen Lab[1]. Researchers from the Citizen Lab used several reverse engineering techniques to analyze a program and decrypted its downloaded keyword lists. By using tools for finding cryptographic constants inside a program's address space as it is running (Knockel et al., 2015), they identified the files that stored keywords for censorship and the URLs from which keywords updates were downloaded for three most popular live-streaming platforms in China: YY, 9158 and Sinashow[2]. These built-in lists of keywords perform checks to determine if any of these keywords are present in users' chat messages before the messages are sent. If a user's message contains a blacklisted keyword in a chat, his/her message will either be undelivered or replaced by asterisks, and generally accompanied with a warning sign such as "The message you sent contains restricted words. Please try again". Figure 1 provides an example of a censored message on YY that contains keyword "tankman", a reference to the Tiananmen Square Protest. At any time, a platform may update its blacklist as it deems necessary. Official reports[3] show that 90% of the "inappropriate messages" on interactive live-streaming platforms are censored through this type of automated keyword filtering due to its efficiency and timeliness.

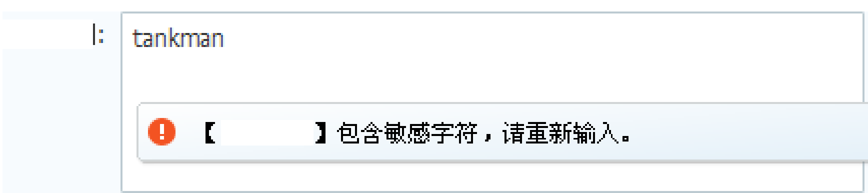


Figure 1: A screen-shot of keyword that triggers censorship on YY.

To uncover the complete history of censorship, the Citizen Lab performed an hourly download and decrypted all three platforms' keyword lists between February 2015 to August 2017.

[1] The Citizen Lab is an interdisciplinary laboratory based at the Munk School of Global Affairs, University of Toronto

[2] For example, Sinashow comes installed with a binary database of keywords in a file named "$Word\_410.ucw$" and downloads updates for it from $http://www.51uc.com/uc\_interface/down\_policy/Word\_410.ucw$. This file is a custom binary container storing sensitive GBK-encoded keywords that have been encrypted (Knockel et al., 2015).

[3] http://www.cac.gov.cn/2017-02/21

A total of 18,655 unique keywords[4] were uncovered from the blacklists of all three platforms. The Citizen Lab used a combination of machine and human translation to translate the keywords to English and analyzed the context behind each one. Based on these translations and contextual information, three researchers coded each keyword into one of 80 content categories grouped under 6 general themes based on a codebook developed in Crandall et al. (2013). Table 1 provides some example categories of keywords[5] grouped into each theme.

Table 1: Content Themes and Related Categories

Theme	Example categories	Example keywords and translations
Event	Recurring events	"64 memorial" (悼念 64)
	Unexpected events	"ZhouYongkang Arrest" (周永康被抓)
Social	Gambling, illicit goods and services	"Crystal meth formula" (冰毒配方)
	Prurient interests	"Adult video" (成人视频)
Political	Communist Party of China	"Inner-party division" (党内分歧)
	Religious movements	"Dalai Lama" (达赖喇嘛)
	Ethnic groups	"East Turkistan Muslim" (东突穆斯林)
Technology	General technical terms	"Internet TV software" (网络电视软件)
	URLs	"app.box.com", "freelibs.org"
	Applications and services	"VPN800", "Encryption Router" (加密路由器)
People	Government officials	"Xi Jinping" (习近平),
		"Ruthless Xi"(包子心狠手辣)
	Dissidents	"Wuerkaixi" (吾尔开希)
Misc	Keywords with unclear contexts	"Too well" (太恩)

The blacklisted keywords target a variety of content including issues related to sensitive events, Chinese politics, circumvention tools, pornography, gambling, and illegal drugs. However, the government often monitors the compliance of censorship during key moments when the information has the greatest impact, such as during elections, periods of civil unrest, and sensitive political anniversaries (Crandall et al., 2013). This study thus focuses on the keywords grouped into the "event" category. Keywords in this category reference to 49 unique events. I extracted the event dates from major news outlets and cross-checked them with Wikipedia entries, if available. The Appendix (Table 9 and Table 10) section provides

[4] including phone numbers and URLs.

[5] In Chinese, words are simply concatenated together whereas English words are separated by whitespace or punctuation. Therefore, these Chinese keywords on the blacklists convey information much the same way as English phrases do.

a detailed description and reference links for each event included in this study. Based on the event dates, I separate these events into two distinct groups: unexpected and recurring events.

1. **Unexpected** events (e.g. South China Sea disputes): if the event originally occurred after May 2015.

2. **Recurring** events (e.g. Memorial day of Tiananmen Protest): if the event originally occurred before May 2015.

Among the 49 unique events, 30 of them are "unexpected" events and the rest 19 are "recurring" events. If a platform added any keywords to its blacklist related to an event on a specific date, that particular event is defined to be "censored" by this platform on that calendar day. In the empirical analysis, I will treat these two types of events separately for two reasons: (1) since both users and platforms may anticipate the (anniversary) date of recurring events, platforms may need to add related keywords days prior to the event date; (2) for some recurring events, related keywords remain in platforms' blacklists from previous calendar years. Even if these platforms do not add any new words during the anniversary, the pre-existing keywords would remain in effect of censoring. Therefore the number of existing keywords may be negatively correlated with the number of keywords added during the event window for a recurring event. While the keywords in other categories such as "social", "political" and "people" also convey contextual information on a platform's censorship behavior, they are mostly generic terms that fail to be associated with any particular event and hence do not fit into the event-study framework. In addition, I consider only the timing of a keyword first *added* to a platform's blacklist and disregard other subsequent operations such as deletion. This is for two reasons: first, the data shows that only a small fraction ($< 0.5\%$) of keywords were added then removed *within* a month; second, adding keywords affects users' experience explicitly by warding off their messages, while the effect of deleting keywords is more subtle and most users are not even aware of this practice unless they try the same word both before and after it was removed.

A secondary dataset on each platform's daily traffic is scraped from Siterankdata.com. It provides the history of websites' global traffic ranks reported by Alexa[6] over a 5-year window. Alexa.com is an American web traffic analysis company that provides web traffic data and global rankings "based on a combined measure of Unique Visitors and Pageviews" on 30 million websites [7]. Specifically, the higher a platform's "rank" is, the less popular it is

[6]© 2018, Alexa Internet (www.alexa.com)

[7]https://support.alexa.com/hc/en-us/articles/200449744-How-are-Alexa-s-traffic-rankings-determined-

on a global scale. In other words, the closer a site is to rank number 1, the more visitors it requires to improve its rank. By contrast, a very small change in the number of visitors to a small site will result in a large change in its rank. Table 2 provides the summary statistics on daily Alexa ranks of all three platforms and their estimated daily unique visitors.

Table 2: Summary Statistics on platform users and Alexa ranks

Platform	Daily Unique Visitors (est.)		Daily Alexa Rank	
	(5/30/2015 - 8/11/2017)			
	Mean	Std. Dev	Mean	Std. Dev.
Big (YY)	6,417,513	3,143,050	7,872	3,083
Medium (9158)	168,088	54,944	84,439	21,694
Small (Sina Show)	5,052	1,035	866,260	972,498

I use the log of the inverse of a platform's global ranking as a proxy for user traffic because studies have shown that the ranking of a website follows Zipf's law (Adamic, 2000): the relationship between the number of visitors to a platform and its global rank by popularity is nearly linear on a log-log plot, with the slope being -1.

3.2 Institutional Background

The market structure of online platforms and the institutional environment of censorship in China offer a particularly suitable setting to study the question of interest in this paper for three reasons. First, rather than passively executing orders of the "big brother", social media companies in China are indeed an intermediary of censorship. Specifically, they have a degree of flexibility in determining *when and what* specific content to block, despite the legal and regulatory pressure from the government (Knockel et al., 2015). In fact, "domestic censorship in China is deeply fragmented and decentralized" (Bamman et al., 2012). The Chinese government directs companies to censor their own content according to a list of vague guidelines (Stern and Hassid, 2012). As a result, private companies are held accountable for any content published on their own platforms: the fact that a story has already been published elsewhere, and therefore presumably approved by the authorities, provides no legal cover ((Initiative, 2005); Human Rights Watch (2006); King et al. (2013)). Second, online platforms in China are subject to a high frequency of censorship requests due to the frequent occurre,nce of unexpected politically sensitive events. This makes it empirically possible to study platforms' interaction and detect potential strategic responses. Third, while network externalities are clearly significant in all social media markets, different social media categories exhibit widely varying levels of concentrations. In some markets, we observe the emergence of a dominant site, whereas, in other markets, competing firms are able to coexist with differentiated positions despite strong network externalities (Zhang and Sarvary, 2011).

3.3 Interactive live-streaming market

This paper studies three social media platforms that operate in an interactive live-streaming market: YY, 9158 and Sinashow. YY is developed by YY Inc. and is the largest live-broadcasting platform in China in terms of its user population. Tian Ge Interactive Holdings Limited owns and operates two other platforms: 9158 and Sina Show. Not only do the two companies list each other as close competitors on their websites for investors, but they are also both market leaders: by revenue, YY owns a share of 40% and Tian Ge 28% in 2014[8]. In addition, approximately 9% of 9158 users are active on both platforms: 9158 and YY[9]. Although Sina Show and 9158 are owned by the same parent company, they do not use the same blacklist of keywords[10] To simplify the notation, I will refer to YY, 9158, and Sina Show as the big, medium, and small platform respectively in all subsequent sections.

With a major focus on music and entertainment, all three platforms engage users in real-time online group activities through voice, video, and text on PC and mobile devices. Their business model also includes monetizing through the sale of virtual goods which keep users actively engaged (Knockel et al., 2015). On YY, for example, users exchange "virtual roses" as a form of currency, with top users said to spend as much as $20,000 per month[11]. Censorship disrupts online activity at some non-negligible cost because the profitability of these platforms highly depends on the active engagement of the users.

4 Event Study Analysis

During normal times, a platform may implement censorship on a specific date for various reasons: a surge in users' messages of sensitive content, the preference of a platform owner,

[8]See statistics from "Corporate Presentation of YY Inc. July 2015".

[9]See statistics from qianfan.analysis.cn.

[10]The Jaccard similarity coefficient between the blacklists of Sina Show and 9158 (i.e. the size of the intersection of two sets divided by the size of their union) is less than 0.4 (Knockel et al., 2015).

[11]https://www.forbes.com/sites/tomiogeron/2012/06/11/yy-com-chinas-unique-real-time-voice-and-video-service-with-a-virtual-goods-twist

local surveillance, etc. It is thus difficult to identify the impact of censorship on platforms' traffic due to endogeneity issues: often times a platform's censorship decision is triggered by its own abnormal traffic. However, an outbreak of nation-wide events, especially the "unexpected" ones, can be considered as exogenous shocks that trigger a platform's self-censorship. Analyzing changes in the number of keywords associated with an event over time provides insight into how these platforms respond to dynamic political and social events through updates to the keyword lists. I adopt an event-study approach to test for such trends. Due to the reasons mentioned in Section 3.1, I will focus only on the "unexpected events" to avoid confounding effects. The event-study results show that while the largest platform censors more words on average, it also responds faster than the smaller platforms. All the platforms have experienced a significant decline in its post-event traffic, but their traffic reverts back to the pre-event level on average two weeks following censorship.

4.1 Censorship Behavior

In order to understand the censorship behavior of platforms following a sequence of unexpected events, I consider the following econometric model:

$$R^i_{ed} = \sum_t \beta^i_t D^t_{ed} + \phi_q + \chi_e + \varepsilon^i_{ed} \tag{1}$$

where R^i_{ed} denotes the number of keywords associated with event e censored by platform $i(=1,2,3)$ on calendar day d[12], ϕ_q is a quarter (seasonal) fixed effect and χ_e is an event fixed effect. The D^t_{ed} are a series of "event-time" dummies that equal one when the calendar day d is within t weeks of event e. Therefore, β^i_t represents the time trend of the number of keywords censored by platform i relative to the event dates, conditional on seasonal and event fixed effect. Formally, we may write:

$$D^t_{ed} = \mathbb{1}\left[t = \lfloor \frac{d - t_e + 3}{7} \rfloor\right]$$

where $\mathbb{1}[.]$ is an indicator function for the expression in brackets being true and t_e is the date when an event $e \in \{E_1, E_2, ..., E_{30}\}$ occurred. Figure 2 gives a visual illustration of how the event-time dummy variables are constructed relative to the calendar dates.

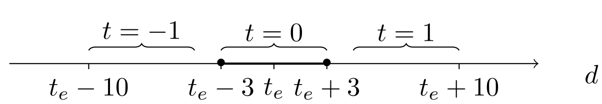


Figure 2: An illustration on defining the event-time dummy variables

[12] $d = 0$ on 05/30/2015, $d = 1$ on 05/31/2015, ... , $d = 808$ on 08/15/2017.

It is known that not all βs can be identified as the dummy variables are perfectly collinear in the presence of event fixed effects. Hence I normalize $\beta_{-1} = 0$. All post-event coefficients can be thought of as treatment effects relative to one week before the event occurs. I also impose endpoint restrictions on β_t^i:

$$\beta_t^i = \begin{cases} \bar{\beta} & \text{if } t \geq 8 \\ \underline{\beta} & \text{if } t \leq -8, \end{cases}$$

which assumes that any dynamics wears off after 8 weeks. Because the sample is unbalanced in event time, these endpoint coefficients give unequal weight to events that happen very early or very late in the sample. For this reason, I restrict the sample to a seven-week window prior to and after each event.

4.2 Platform Traffic

In order to study the trend of platforms' traffic or popularity in the aftermath of these events, I consider a similar econometric model as in the last section except that the dependent variable X_{ed}^i now denotes the log of user size (i.e. log (1/Alexa rank)) of platform i on calendar day d. Specifically, I consider the following model

$$X_{ed}^i = \sum_t b_t^i D_{ed}^t + \phi_q + \varepsilon_{ed}^i. \tag{2}$$

If events are indeed "unexpected" to a platform (and their users), the following null hypothesis should be true:

$$H_0 : b_t^i = 0, \forall t < 0, i = 1, 2, 3$$

In other words, the above condition states that there should be, on average, no trends of platform-specific traffic preceding these events. I test this hypothesis using robust standard errors clustered at the event level. Table 3 reports the test statistics for the joint significance

Table 3: Joint test statistics of pre-event coefficients

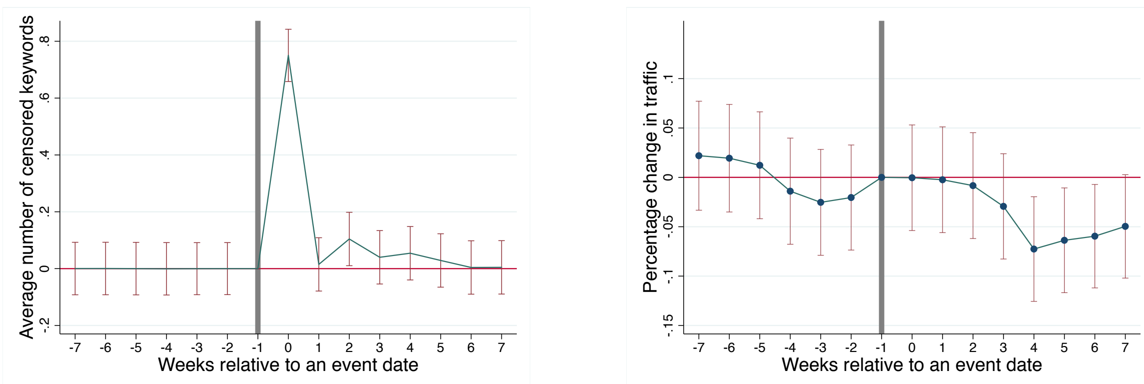
Platform i	Null Hypothesis	F statistics	p-value
1 (Big)	$b_{-1}^1 = b_{-2}^1 = ... = b_{-7}^1 = 0$	0.86	0.5414
2 (Medium)	$b_{-1}^2 = b_{-2}^2 = ... = b_{-7}^2 = 0$	1.02	0.4154
3 (Small)	$b_{-1}^3 = b_{-2}^3 = ... = b_{-7}^3 = 0$	0.64	0.7201

of pre-event coefficients for each platform. All three F-statistics fail to reject the null hypothesis, suggesting that there is no pre-event trend in traffic. This result implies that the event classification scheme mentioned in Section 3.1 provides relatively accurate information about the dates of unexpected events.

4.3 Event Study Results

Figures 4-3 plot the estimated censorship (β_t^i) and traffic coefficients (b_t^i) of each platform i from the regressions given in Equation (1) and Equation (2) respectively. The bands around the point estimates are 95 percent robust confidence intervals.

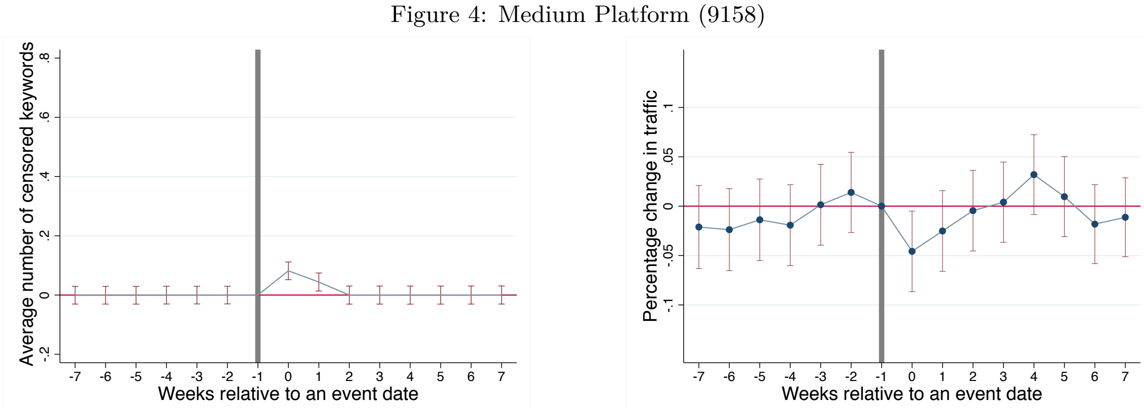
Figure 3: Big Platform (YY)



(a) Average Number of Keywords Censored

(b) Percentage Change in Traffic

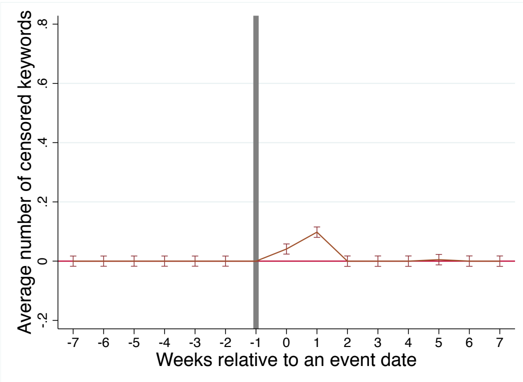
Figure 4: Medium Platform (9158)



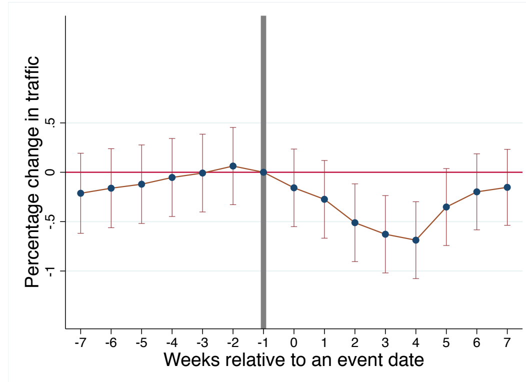
(a) Average Number of Keywords Censored

(b) Percentage Change in Traffic

Figure 5: Small Platform (Sina Show)



(a) Average Number of Keywords Censored



(b) Percentage Change in Traffic

Three facts are revealed from the event study results of the platform's censorship behavior (left panel) and traffic (right panel). First, the big platform censors on average more keywords and also reacts faster than the smaller ones (i.e. $\beta_1^0 > \beta_2^0 > \beta_3^0 > 0$). Specifically, the smallest platform has delayed censoring most keywords to the week after an event (i.e. $\beta_3^1 > \beta_3^0$). Second, all three platforms have experienced a significant decline in the post-event traffic, but this decline happened to platforms of different sizes at varying magnitude and times. In particular, the medium platform's traffic decreased by less than 5% immediately after an event occurred, while the big platform's traffic began to decline only 4 weeks after an event occurred. In addition, the small platform lost almost 50%[13] of its users around two weeks after the event occurred. Note that the timing order of each platform's post-event traffic mirrors that of their censorship decisions. These results suggest that a platform's user traffic is negatively affected by its own censorship decision. Finally, a platform's traffic reverts back to the pre-event level on average two weeks following its original decline.

[13]This drastic change in the traffic of small platforms is likely caused by the measurement error of Alexa ranks. This is because a very small change in the number of visitors to a small site will result in a large change in its rank.

5 A Structural Model of Strategic Censorship

The event-study analysis shows that platforms of different sizes censor at different times and intensities and their traffic is reponsive to the censorship activity. In this section, I explicitly model how users on each platform may stay or switch to another platform conditional on their preferences and allow platforms to strategically exploit users' switching patterns, anticipating their competitors' censorship decisions.

5.1 Platform payoffs

Consider a market with $N \geq 2$ platforms. Each platform is indexed by $i(= 1, 2, .., N)$ and let $-i$ denote the set of i's opponents. Every time an unexpected event occurs, I consider platforms playing an independent game, where each platform simultaneously makes a decision about whether to add keywords within 1 week of event occurrence or not[14]. Hence platform i has a decision variable $a_i \in \{0, 1\}$ denoting its decision to censor (1) or not (0). They gain utility from the mass of users they would retain after an event, where the dollar value of each user is normalized to 1. I assume that users will return to their favorite platforms before the next event occurs, and refer to them as the "captive audience". This assumption is supported by the event-study results: platforms' traffic reverts back to the pre-event level on average two weeks following censorship. Common factors, such as the political risk of not censoring a specific event, are factored in by assuming that not censoring is, on average, less attractive to platforms conditional on their share of users. Let platform i's payoff (π_i) from censoring and not censoring be:

$$\pi_i = \begin{cases} D_i(a, x) & a_i = 1 \\ D_i(a, x) - (c_0 + c_1 x_i + \varepsilon_i) & a_i = 0, \end{cases}$$

where $D_i(a, x)$ is the remaining mass of users on platform i conditional on the censorship decisions of each platform and their competitors. The terms in the parentheses $(c_0 + c_1 x_i + \varepsilon_i)$ reflect the political cost of not censoring an event, which is assumed to be a linear function of x_i, the mass of "captive audience" of platform i. c_0 can be viewed as a fixed penalty from non-compliance, while c_1 is the probability of a temporary shut-down by the government. ε_i is the private signal observed only by the platform i but signals are allowed to be correlated across platforms. The joint distribution of these private signals are assumed

[14] This assumption is motivated by the event-study result that most keywords were censored within 1 week of event occurrence if platforms censor at all.

to be known by all platforms. The correlation between private signals captures the fact that some unobserved event-specific variables may affect all platforms' censorship decisions. This assumption is also motivated by the anecdote that social media companies in China usually receive private information of censorship guidelines from different "resources distributed across several bureaucracies" (Miller (2017)), which, to their awareness, possibly originates from the same central directive. As a result, platforms exploit both their private information *and* the correlation between private information to form a rational expectation of their rivals' choices.

5.2 User switching behavior

There is a mass of 1 users in the market. Each platform i is the favorite of a share of x_i users such that $\sum_{i=1}^{N} x_i = 1$. Before events occur, users are only active on their favorite platform[15]. After an event occurs, users obtain some disutility from being censored calibrated by an individual taste parameter θ. On all platforms, assume that θ is drawn from a Pareto distribution[16] with a shape parameter denoted by $\alpha(> 0)$ and its location parameter normalized to 1. Let $F(\cdot)$ denote the cumulative distribution function of variable θ:

$$F(\theta > \underline{\theta}) = \begin{cases} \left(\frac{1}{\underline{\theta}}\right)^{\alpha} & \underline{\theta} \geq 1 \\ 1 & \underline{\theta} < 1. \end{cases}$$

Upon observing the censorship actions of their own platform, users decide to switch ($s = 1$) or not to switch ($s = 0$) to other platforms. If they choose to stay when the platform censors, depending on their distaste for censorship, they will have to endure some degree of disutility. Alternatively, if they choose to switch, an expected fixed cost of switching $\gamma(> 1)$ is incurred. Prior to switching, users did not know whether other platforms are implementing censorship until they switch and start using it. Thus I assume that users who have switched from platform i will end up using one of its competitor platforms $j(\neq i)$ with equal probability. If switching users find out that the new platform also censors their messages, they will leave the new platform immediately for their outside options, such as watching TV, listening to music, etc. The utility from outside options is normalized to zero. Formally, a user with taste parameter θ from platform i chooses $s \in \{0, 1\}$ to maximize his/her utility conditional

[15]The single-homing assumption is based on the fact that less than .9% of the users have accounts of both YY and 9158 according to the 2015 annual report from Analysis.cn, a Chinese-based consulting company.

[16]This distributional assumption on θ is innocuous. Any distribution that satisfies $F(\theta > 0) = 1$ and $F(\theta > \gamma) > 0$ (e.g. log-normal) will deliver a demand function that is linear in the binary actions (i.e., $a \in \{0, 1\}$) of a firm. For illustrative purpose, I assume θ is drawn from a Pareto distribution as it is scale-free and associated with a simple CDF.

on platforms' censorship actions:

$$\max_{s \in \{0,1\}} u_i(s;\theta) = -(1-s)\theta a_i - s\gamma. \tag{3}$$

A user θ on platform i prefers to switch if and only if $u_i(s=1;\theta) \geq u_i(s=0;\theta)$:

$$\theta a_i \geq \gamma. \tag{4}$$

Let $\underline{\theta_i}(a)$ denote the threshold user on platform i who is indifferent between switching and not switching conditional on platforms' actions. Any user with θ above this threshold will switch or otherwise will stay. Note that if their favorite platform does not censor, no user will switch out as switching is costly (i.e., $\underline{\theta_i}(a) \to \infty$). If the platform does censor, however, only a fraction of users would switch out while the remaining users will stay despite being censored (i.e., $\underline{\theta_i}(a) = \gamma > 1$) . Therefore, for any platform i, the share of "switchers" is given by

$$F(\theta \geq \underline{\theta_i}(a)) = \big(\frac{1}{\underline{\theta_i}(a)}\big)^{\alpha} = \begin{cases} \big(\frac{1}{\gamma}\big)^{\alpha} & a_i = 1 \\ 0 & a_i = 0 \end{cases} \tag{5}$$

Taking log of both sides in equation (5) when $a_i = 1$, we can rewrite it as follows:

$$log[F(\theta \geq \underline{\theta_i}(a_i = 1))] = -\alpha log(\gamma) \tag{6}$$

Based on the above equation, α can be viewed as the "switching elasticity" that characterizes how responsive users are to changes in the switching cost. All else equal, the larger is the switching cost γ, the larger is the fraction of users that will always stay. In sum, the mass of remaining users when platform i chooses a_i and its opponents choose a_{-i} is given by

$$D_i(a,x) = x_i - \underbrace{x_i F(\theta \geq \underline{\theta_i}(a))}_{\text{outgoing users}} + \underbrace{(1-a_i)\sum_{j \neq i} x_j \frac{1}{N-1} F(\theta \geq \underline{\theta_j}(a))}_{\text{incoming users}}, \tag{7}$$

which depends on the relative size of outgoing and incoming users, affected by both i and its competitors' actions. Plugging equation (5) into equation (7), we obtain the following demand function:

$$D_i(a,x) = \begin{cases} x_i - x_i\big(\frac{1}{\gamma}\big)^{\alpha} & a_i = 1 \\ x_i + \sum_{j \neq i} \frac{x_j}{N-1}\big(\frac{1}{\gamma}\big)^{\alpha} a_j & a_i = 0 \end{cases}$$

Specifically, given the private signal ε_i, platform i's payoff when censoring relative to not censoring can be expressed as follows,

$$\pi_i(a_i = 1, a_{-i}, x) - \pi_i(a_i = 0, a_{-i}, x) = \beta_0 + x_i\beta_1 + \sum_{j \neq i} \delta_j(x) a_j + \varepsilon_i \tag{8}$$

where

$$\beta_0 = c_0 \tag{9}$$

$$\beta_1 = c_1 - \gamma^{-\alpha} \tag{10}$$

$$\delta_j(x) = -\frac{x_j}{(N-1)(\gamma)^{\alpha}}. \tag{11}$$

Note that the platform i will choose $a_i = 1$ iff Equation (8) is positive. Therefore we can rewrite the utility function of platform i into the following relative form:

$$v_i(x) = \begin{cases} \beta_0 + \beta_1 x_i + \sum_{j \neq i} \delta_j(x) a_j + \varepsilon_i & \text{if } a_i = 1 \\ 0 & \text{if } a_i = 0 \end{cases} \tag{12}$$

Note that equation (12) corresponds to the reduced-form profit function widely adopted in the existing literature on social interactions (e.g. Bajari et al. (2006); De Paula and Tang (2012); Aradillas-Lopez and Gandhi (2013)), and $\delta_j(\cdot)$ is referred to as the "strategic interaction" term which can be expanded into a function of platforms' user size scaled by some structural parameters. Since $\delta_j(x) < 0$ for any given state variable $x \in \Omega_X$, a_j is clearly a strategic substitute for a_i. Furthermore, conditional on the size distribution of platforms, the magnitude of strategic interaction is larger when users' switching cost (γ) is smaller or the "switching elasticity" (α) is larger. This is because the larger are the two parameters, the more likely a bigger proportion of users would switch to a competitor platform that does not censor. Under these circumstances, a platform's choice of censorship is more sensitive to its competitors' actions.

5.3 Bayesian Nash Equilibrium Strategies

Without loss of generality, this paper assumes that the outcome observed is the result of a pure strategy BNE[17]. In this game, each platform ($i = 1, 2, ..., N$) simultaneously chooses $a_i \in \{0, 1\}$. A state of the game is described by (X, ε), where $X = (X_1, X_2, ..., X_N)$ and $\varepsilon = (\varepsilon_1, \varepsilon_2, ..., \varepsilon_N)$. $X_i \in (0, 1]$ is platform i's user share prior to an event that is publicly observed. $\varepsilon_i \in \mathbb{R}$ is the private signal observed only by platform i. Let $F_{\varepsilon|X}$ be the conditional distribution function of ε given X. Let $\Omega_X \equiv \{(X_1, X_2, ..., X_N) | \sum_{i=1}^{N} X_i = 1\}$ denote the support of X. In equilibrium, platform i chooses action 1 if and only if its expected payoff

[17] It is well known that Harsanyi's purification theorem have endorsed the empirical appeal of pure strategy equilibria. Harsanyi (1973) has shown that the existence of private information in payoffs will induce players using pure strategies approximately with the prescribed probabilities associated with mixed-strategy equilibria of a complete information game.

is greater than if it chooses action 0, i.e.,

$$a_i = \mathbb{1}\left[\beta_0 + x_i\beta_1 + \sum_{j\neq i}\delta_j(x)\cdot\mathbb{P}(a_j = 1|X, \varepsilon_i) + \varepsilon_i \geq 0\right] \tag{13}$$

where $\mathbb{1}[\cdot]$ is the indicator function. The term $\mathbb{P}(a_j = 1|X, \varepsilon_i)$ is platform i's expectation on its rival j's action, based on player i's private information and the publicly-observed state variable. Equation (13) defines a set of simultaneous equations. Following Athey (2001) and Wan and Xu (2014), this paper adopts a particular class of BNEs referred to as "monotone pure strategies" (MPSEs). With an MPSE[18] in this framework, there exists a sequence of cutoffs $\varepsilon^* = (\varepsilon_1^*, \varepsilon_2^*, ..., \varepsilon_N^*) : \Omega_X \to \mathbb{R}^N$ such that for each player i,

$$a_i = \mathbb{1}\left[\varepsilon_i \geq \varepsilon_i^*(X)\right]. \tag{14}$$

That is, if the private shock (i.e. the private cost of not censoring a particular event) is sufficiently large, platform i will choose to censor, i.e., $a_i = 1$. Athey (2001) proves that an MPSE exists whenever a Bayesian game obeys a Spence-Mirrlees single-crossing condition. Hence in this model I consider the following assumptions made to ensure the single-crossing condition.

Assumption 1. *(Bounded Positive Regression Dependence) The conditional pdf $f_{\varepsilon|X}$ exists and is assumed to be common knowledge. For any $i \in \{1, 2, ..., N\}$ and $(t, x) \in \mathbb{R} \times \Omega_X$,*

$$0 \leq \frac{\partial\mathbb{P}(\varepsilon_{-i} \geq t|X = x, \varepsilon_i)}{\partial\varepsilon_i} \leq (N-1)(\gamma)^\alpha - \left|\frac{\partial\mathbb{P}(\varepsilon_{-i} \geq t|X = x, \varepsilon_i)}{\partial t}\right|.$$

Assumption 1 implies that platform i's best response is non-decreasing in its private signal when its rivals also adopt a monotone strategy. In a parametric case where ε conforms to a joint normal distribution with mean zero and unit variance, it suffices that the correlation coefficient between ε_i and ε_j is bounded above, vis-a-vis the magnitude of $(N-1)(\gamma)^\alpha$.

Theorem 1. *If Assumption 1 holds, then for any public state variable $x \in \Omega_X$, there exists a unique MPSE where each player's equilibrium strategy is non-decreasing.*

Proof. See Appendix. □

Given that the equilibrium is monotone conditional on $X = x$, platform i receives zero expected payoff when the value of its private shock equals $\varepsilon_i^*(x)$, that is,

$$\varepsilon_i^*(x) = -c_0 - (c_1 - (\gamma)^{-\alpha})x_i + \sum_{j\neq i}\frac{x_j}{(N-1)(\gamma)^\alpha}\mathbb{P}\left[\varepsilon_j \geq \varepsilon_j^*(x)|\varepsilon_i = \varepsilon_i^*(x)\right] \tag{15}$$

Let $\mathbb{P}(\varepsilon_i \geq \varepsilon_i^*(x))$ denote the equilibrium probability of censorship for platform i.

[18] Note that if private signals are assumed to be independent, all BNE solutions to this game are MPSEs.

5.4 Comparative Statics

In this section, I describe how the equilibrium strategy of a platform as well as the market-level compliance varies with respect to changes in market structure. To present the results in a tractable fashion, I assume that the private shocks follow a mean zero multivariate normal distribution with variance equal to 1 and a correlation coefficient denoted by ρ. Private shocks are assumed to be independent of the public state variable. I begin by analyzing how a platform's equilibrium strategy is affected by the number and size of its competitors. Then I describe the impact of market concentration on market-level compliance through comparing the scope of censorship across different markets. The model predicts a higher scope of censorship as the market becomes more concentrated.

5.4.1 Firm-level compliance

Proposition 1. *(**Number of Competitors**) When the political pressure is sufficiently high, a platform is less likely to censor if there are more identical competitors in the market. That is, for any $N \geq 2$ and $\forall j \neq i, x_i = x_j = \frac{1}{N}$, if $c_1 > \frac{3}{2}\gamma^{-\alpha} + \max\{0, -Nc_0\}$, then*

$$\frac{\Delta \mathbb{P}(\varepsilon_i \geq \varepsilon_i^*(x))}{\Delta N} < 0.$$

Proof. See Appendix. □

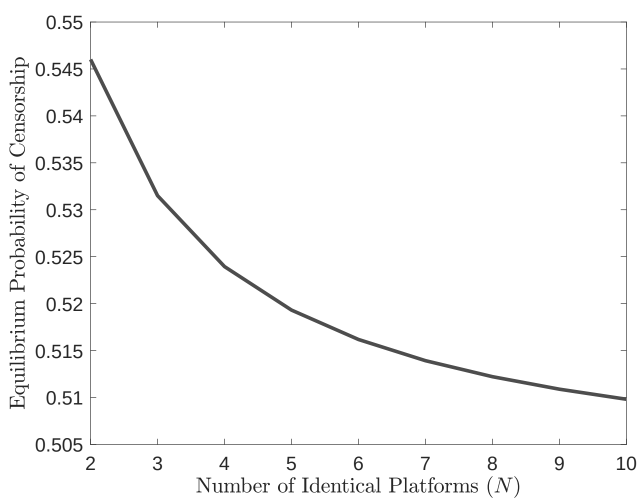


Figure 6: Equilibrium Probability. vs. Number of Competitors

As a market accommodates more platforms, two factors are at play: on the one hand, each platform hosts a smaller share of users and thus bears less cost of not censoring; On the other hand, each platform has fewer incentives to differentiate from others by not censoring because chances are smaller that users who have switched from one's competitors will end up on one's own platform, as users have increasingly many alternatives to choose from. When the political pressure is sufficiently high, the former incentive dominates the latter. As a result, platforms censor less often in a market with more competitors.

Proposition 2. *(**Correlation between Private Signals**) When competitors are of identical size, a platform is less likely to censor in smaller markets if its private signal is more correlated with that of its competitors ($\rho \uparrow$). In other words, for any $\forall 1 \leq i \leq N$ and $x \in \Omega_X$ such that $\forall j \neq i, x_i = x_j = \frac{1}{N}$,*

$$\frac{\partial \mathbb{P}(\varepsilon_i \geq \varepsilon_i^*(x))}{\partial \rho} \begin{cases} < 0 & \text{if } c_1 < \frac{3}{2}\gamma^{-\alpha} - Nc_0 \\ \geq 0 & \text{if } c_1 \geq \frac{3}{2}\gamma^{-\alpha} - Nc_0 \end{cases}.$$

Proof. See Appendix. □

Counter-intuitively, increasing the correlation between platforms' private shocks may reduce their incentive to censor when there are few platforms in the market. This is because a platform's own signal not only indicates the cost of its own censorship but also reveals information about its competitors' strategy which is monotonically increasing in one's private signal. Therefore, if a platform receives a high signal for censoring early and the correlation between signals is high, the platform would predict that its competitors must have received a similarly high signal and thus more likely to censor early. Knowing this, a platform has an incentive not to censor because its action is a strategic substitute for that of its competitors (i.e. $\delta(\cdot) < 0$). This strategic incentive is stronger in smaller markets.

Proposition 3. *(**Size of Competitors**) When the political pressure is sufficiently high, a small platform censors less often than its big competitor. That is, if $c_1 > \gamma^{-\alpha}$, then $\forall x_i < x_j$,*

$$\mathbb{P}(\varepsilon_i \geq \varepsilon_i^*(x)) < \mathbb{P}(\varepsilon_i \geq \varepsilon_j^*(x)).$$

Proof. See Appendix. □

Since the magnitude of one's strategic incentive depends on both the size and action of one's competitors, platforms of different sizes have rather different incentives to censor. When a platform captures a larger user share, it not only bears a higher political cost of not censoring which is proportional to its user size but also higher loss from censoring due to its switching users. The former cost dominates the latter loss only when the political pressure is sufficiently high, which motivates the bigger platforms to censor more often. As a result, a small platform benefits more from not censoring because they can attract switching users from their bigger competitors who are now even more likely to censor.

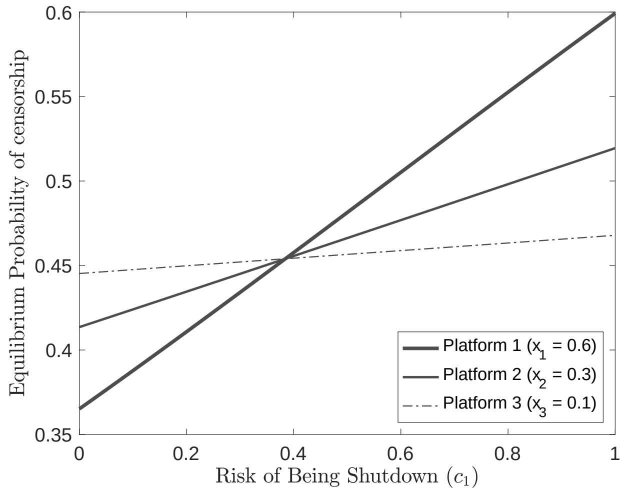


Figure 7: Equilibrium Probability vs. Political Pressure

Figure 7 shows how equilibrium censorship probability of each platform changes as the political cost of not censoring c_1 varies from 0 to 1, with the other parameters held fixed at $c_0 = 0, (\gamma)^{-\alpha} = 0.5$ and $\rho = 0.2$. The biggest platform has 60% of user share and two other smaller platforms (2 and 3) have a user share of 30% and 10% respectively.

5.4.2 Scope of censorship

In the previous subsection, I have described how each platform's equilibrium strategy varies with respect to market covariates. However, upstream players, such as a regulator or an authoritarian government, are generally more concerned about the overall share of users who are affected by censorship in the entire market. To measure the market-level compliance, I define an index for the scope of censorship which equals the expected share of users affected by censorship during a salient event. Specifically, in a market of N platforms, the index is defined as follows:

$$SC = \mathbb{E}\left(\sum_{i=1}^{N} x_i a_i(x)\right). \tag{16}$$

Proposition 4. ***(Market Concentration on Scope of Censorship)*** *Suppose there are N platforms in markets A and B. Let HHI_A and HHI_B denote the Herfindahl-Hirschman index of market A and B respectively. Let SC_A and SC_B denote the scope of censorship in the* *respective market. If* $c_1 > \frac{3}{2}\gamma^{-\alpha} + \max\{0, -Nc_0\}$*, then* $HHI_A > HHI_B \implies SC_A > SC_B$*. In other words, when political pressure is sufficiently high, a user is more likely to experience censorship as the market becomes more concentrated.*

Proof. See Appendix. □

When the number of platforms remains unchanged, if a platform becomes larger and more likely to censor, at least one of its competitors would become smaller and obtain more strategic incentives to differentiate by not censoring. The latter competitive effect puts downward pressure on the scope of censorship, whereas the former political pressure contributes to a broader scope of censorship. When the political pressure is sufficiently high, the behavior of a large platform dominates and users are more likely to experience censorship as the market becomes more concentrated.

Alternatively, if a market becomes concentrated by hosting fewer platforms, two factors are at play: first, each platform captures a larger market share and bears higher political costs of non-compliance; second, each platform has more strategic incentives to differentiate from other obedient competitors by not censoring, now that users have fewer options to switch to. Following this change in the market structure, whether a platform is more or less likely to censor during the next salient event depends on which of the two forces dominates. If even a slight increase in a platform ’ s size alarms the government and significantly raises its risk of non-compliance, the former political pressure would dominate and generate more censorship in the marketplace. If, on the other hand, limiting the number of alternatives significantly increases a platform's chance to capture switching users, then the latter strategic incentive would dominate and cause platforms to censor less often in equilibrium.

To quantify the relative magnitude of these two forces in my empirical context and draw policy-relevant counterfactual predictions, I proceed in the next section by taking the model to data.

6 Empirical Methods

This section discusses the empirical strategies of estimating the model, and then illustrates the estimators' finite sample performance through a Monte Carlo experiment. I consider each event in the data as an independent game and assume that the parameters in my model does not change across different games. Platforms are considered as non-differentiated except for their market share[19]. I measure platforms' market share by their respective traffic one week prior to an event. A platform is defined to have censored an event if and only if it added any keywords related to an event within the first week of event occurrence. I identify the parameters associated with the political incentive by exploiting the variations in platforms' own traffic across different events and the strategic incentive by exploiting the variations in their competitors' traffic across different events. The latter is conditional on the existence of exclusion restriction in this model: changes in the size of a competitor platform only affects the platform's choice probabilities through the strategic interaction term. I show that the model parameters $(c_0, c_1, \gamma^{-\alpha})$ are identified up to scale without imposing further parametric assumptions on the error structure.

6.1 Identification

I now formally describe the identification strategy in this subsection. The identification strategy follows Wan and Xu (2014) and takes two steps: first, I show that estimable bounds for the equilibrium beliefs can be derived under Assumption 1 and they can be arbitrarily close to each other if there exists one regressor that has sufficiently large independent variations (Lemma 1). Second, I show that $(c_0, c_1, (\gamma)^{-\alpha})$ is point identified up to scale by following Manski and Tamer (2002)'s interval–observed regressor approach.

Theorem 2. *If Assumption 1 holds, this structural model can be represented as a semi-parametric binary regression model where*

$$a_i = \mathbb{1}[\varepsilon_i \geq -\beta_0 - \beta_1 x_i - \sum_{j \neq i} \delta_j(x)\sigma_{ij}(x)], \forall i = 1, 2, .., N \tag{17}$$

and

$$\mathbb{P}(\sigma^0_{ij}(x) \leq \sigma_{ij}(x) \leq \sigma^1_{ij}(x)) = 1 \tag{18}$$

where

$$\begin{aligned}
\sigma_{ij}(x) &\equiv \mathbb{P}(\varepsilon_j \geq \varepsilon^*_j(x)|X = x, \varepsilon_i = \varepsilon^*_i(x)) \\
\sigma^0_{ij}(x) &\equiv \mathbb{P}(\varepsilon_j \geq \varepsilon^*_j(x)|X = x, \varepsilon_i < \varepsilon^*_i(x)) \\
\sigma^1_{ij}(x) &\equiv \mathbb{P}(\varepsilon_j \geq \varepsilon^*_j(x)|X = x, \varepsilon_i \geq \varepsilon^*_i(x))
\end{aligned}$$

Proof. This proof extends Theorem 1 in Wan and Xu (2014) to N players. See Appendix. □

[19] Due to data limitation, I have abstrated away from other factors that differentiate these platforms and assumed that those factors are orthogonal to platforms' censorship decisons

Note that the bounds $\sigma_{ij}^0 = \mathbb{P}(a_j = 1|X = x, a_i = 0)$ and $\sigma_{ij}^1 = \mathbb{P}(a_j = 1|X = x, a_i = 1)$ are non-parametrically estimable[20].

Lemma 1. *For any $\epsilon > 0$ and $x_i \in \Omega_{X_i}$,*

$$\lim_{t \to 1} \mathbb{P}\left(\sigma_{ij}^1(X) - \sigma_{ij}^0(X) \geq \epsilon | X_i = x_i, X_j = t\right) = 0$$

Lemma 1 shows that the non-parametrically estimable upper and lower bounds for the equilibrium beliefs can be arbitrarily close to each other when one of the platforms captures a dominant market share.

Proof. See Appendix. □

Assumption 2. *$Median(\varepsilon_j|X = x) = 0$ for all $x \in \Omega_X$.*

Assumption 2 allows for heteroskedasticity of unknown form.

Assumption 3. $\beta_1 \neq 0$. *The distribution of X_i conditional on X_{-i} has everywhere positive density with respect to the Lebesgue measure.*

Assumption 3 requires that for each platform, there exists a special regressor that is continuously distributed and has unbounded support conditional on the rest of regressors. This assumption implies an exclusion restriction. According to Theorem 2 from Wan and Xu (2014), $(\beta_0, \beta_1, \delta)$ is pointed identified up to scale if Assumptions 1 - 3 hold. Recall that in my framework,

$$\beta_0 = c_0 \tag{19}$$

$$\beta_1 = c_1 - \gamma^{-\alpha} \tag{20}$$

$$\delta = -\frac{1}{(N-1)(\gamma)^\alpha}. \tag{21}$$

Therefore, (c_0, c_1) is point identified when we normalize $(\gamma)^{-\alpha} = 1$.

6.2 Estimation Methods

This section describes the estimation strategy. I begin by presenting two different estimation procedures, before discussing their respective strengths and weakness.

[20]Moreover, they collapse to be one, i.e., $\sigma_{ij}^0(X) = \sigma_{ij}^1(X)$ if and only if ε_i and ε_j are independent conditional on X for any $i \neq j$.

6.2.1 Two-step Modified Maximum Score Estimation

The modified maximum score estimation (MMSE) follows the procedure proposed in Wan and Xu (2014). The estimation takes two steps. First, I non-parametrically estimate upper and lower bounds $(\sigma_{ij}^0, \sigma_{ij}^1)$ for each pair of platform i and j, the density weights f_X and platforms' marginal choice probabilities; Second, I estimate the structural parameters from a maximum score type objective function. Suppose that Assumption 1-4 are satisfied and let $\theta_0 \equiv (c_0, c_1)$, then

$$\theta_0 = \arg\max_{\theta\in\Theta} \mathcal{L}(\theta),$$

where $\mathcal{L}(\theta) = \sum_{i=1}^N \mathbb{E}\left[(2a_i - 1) \times f_X(X) \times \xi_i\right]$ and the function ξ_i is defined by

$$\begin{aligned}\xi_i = {} & g_i(X) sgn\left[c_0 + (c_1 - 1)X_i - \sum_{j\neq i}\left(\frac{1}{N-1}\right) X_j \sigma_{ij}^0(X)\right] \\ & + (1 - g_i(X)) sgn\left[c_0 + (c_1 - 1)X_i - \sum_{j\neq i}\left(\frac{1}{N-1}\right) X_j \sigma_{ij}^1(X)\right]\end{aligned}$$

where $g_i(X) = \mathbb{1}\left[\mathbb{P}(a_i = 1|X = x) \geq \frac{1}{2}\right]$ and $sgn(\cdot)$ is the sign function. Then I construct a $\mathcal{U}$- process sample analog of the population objective function $\mathcal{L}(\theta)$ following Wan and Xu (2014). Specifically, the estimator for θ_0 is defined as

$$\hat{\theta} = \arg\max_{\theta\in\Theta} \mathcal{U}_G\left(\theta; \hat{\xi}, \hat{\sigma}\right) \tag{22}$$

where

$$\mathcal{U}_G(\theta; \hat{g}, \hat{\sigma}) = \frac{1}{G(G-1)} \sum_{k=1}^G \sum_{l\neq k}^G \sum_{i=1}^N \left\{(2a_{il} - 1) K_h(X_l - X_k) \xi_i(x)\right\} \tag{23}$$

where G is the number of games and $K_h(\cdot) = K(\cdot/h)/h^d$ is a kernel function with smoothing bandwidth h. However, $\mathcal{U}_G(\theta; \hat{g}, \hat{\sigma})$ is an infeasible sample analog because $\sigma_{ij}^0, \sigma_{ij}^1$ and g_i are unknown. To resolve this issue, I plug into their nonparametric estimates $\hat{\sigma}_{ij}^0, \hat{\sigma}_{ij}^1$ and $\hat{g}_i$ respectively. First, I estimate $\hat{\sigma}_{ij}^0$ and $\hat{\sigma}_{ij}^1$ by

$$\hat{\sigma}_{ij}^0(x_k) = \frac{\sum_{l\neq k}^G a_{jl} a_{il} K_h(X_l - x_k)}{\sum_{l\neq k}^G (1 - a_{il}) K_h(X_l - x_k)} + G^{-\frac{1}{2}} \tag{24}$$

$$\hat{\sigma}_{ij}^1(x_k) = \frac{\sum_{l\neq k}^G a_{jl} a_{il} K_h(X_l - x_k)}{\sum_{l\neq k}^G a_{il} K_h(X_l - x_k)} - G^{-\frac{1}{2}} \tag{25}$$

where a_{jl} equals 1 if the platform j censors event l within the first week. The second term $G^{-\frac{1}{2}}$ ensures that $\hat{\sigma}_{ij}^0(x) \leq \sigma_{ij}^0(x) \leq \sigma_{ij}^1(x) \leq \hat{\sigma}_{ij}^1(x)$ with probability approaching one (faster than any polynomial rates). Then I estimate $g_i(x)$ by

$$\hat{g}_i(x_k) = \mathbb{1}\left[\frac{1}{(G-1)}\sum_{l\neq k}^{G}\{2a_{il}-1\}\times K_h\left(X_l - x_k\right) \geq 0\right] \tag{26}$$

The first stage nonparametric estimation error is negligible some additional assumptions on the kernel function K and random vector X mentioned in Wan and Xu (2014). As a result, $\hat{\theta} \xrightarrow{p} \theta_0$.

6.2.2 Nested Fixed Point Estimation

The Nested Fixed Point Algorithm (NFPX) is proposed by Rust (1987). To apply this method, I assume that private signals follow joint normal distribution each with a mean of zero, and variance–covariance matrix Σ, where Σ has values of 1 on the leading diagonal and a correlation coefficient $\rho \geq 0$ as off-diagonal elements. For each iteration, I solve the equilibrium strategies for each platform in the inner loop and use Maximum Likelihood Estimation in the outer loop. Given the state variables $X = (x_1, x_2, x_3)$ and a set of parameter guesses for c_0, c_1, and ρ, I calculate each platform's equilibrium cut-off values (ε_i^*) by iterating on the following system of equations:

$$\varepsilon_i^* = -c_0 - \left(c_1 - (\gamma)^{-\alpha}\right)x_i + \sum_{j\neq i}\frac{x_j\,(\gamma)^{-\alpha}}{N-1}\left[1 - \Phi\left(\frac{\varepsilon_j^* - \rho\varepsilon_i^*}{\sqrt{1-\rho^2}}\right)\right], \forall i = 1, 2, 3, \tag{27}$$

where $\gamma^{-\alpha}$ is normalized to 1. The inner loop iterates until the cutoff values converge to a fixed point. Using the cutoff values, I can construct platforms' choice probabilities and form the joint likelihood function. The joint distribution of platforms' choice probabilities conditional on X, which for notational convenience I abbreviate to $P^{a_1a_2a_3}$, has in total eight elements:

$$P^{111} = \mathbb{P}\left(\varepsilon_1 \geq \varepsilon_1^*(X), \varepsilon_2 \geq \varepsilon_2^*(X), \varepsilon_3 \geq \varepsilon_3^*(X)\right), \tag{28}$$

$$P^{110} = \mathbb{P}\left(\varepsilon_1 \geq \varepsilon_1^*(X), \varepsilon_2 \geq \varepsilon_2^*(X), \varepsilon_3 < \varepsilon_3^*(X)\right), \tag{29}$$

$$P^{100} = \mathbb{P}\left(\varepsilon_1 \geq \varepsilon_1^*(X), \varepsilon_2 < \varepsilon_2^*(X), \varepsilon_3 < \varepsilon_3^*(X)\right), \tag{30}$$

$$P^{101} = \mathbb{P}\left(\varepsilon_1 \geq \varepsilon_1^*(X), \varepsilon_2 < \varepsilon_2^*(X), \varepsilon_3 \geq \varepsilon_3^*(X)\right), \tag{31}$$

$$P^{011} = \mathbb{P}\left(\varepsilon_1 < \varepsilon_1^*(X), \varepsilon_2 \geq \varepsilon_2^*(X), \varepsilon_3 \geq \varepsilon_3^*(X)\right), \tag{32}$$

$$P^{010} = \mathbb{P}\left(\varepsilon_1 < \varepsilon_1^*(X), \varepsilon_2 \geq \varepsilon_2^*(X), \varepsilon_3 < \varepsilon_3^*(X)\right), \tag{33}$$

$$P^{000} = \mathbb{P}\left(\varepsilon_1 < \varepsilon_1^*(X), \varepsilon_2 < \varepsilon_2^*(X), \varepsilon_3 < \varepsilon_3^*(X)\right), \tag{34}$$

$$P^{001} = \mathbb{P}\left(\varepsilon_1 < \varepsilon_1^*(X), \varepsilon_2 < \varepsilon_2^*(X), \varepsilon_3 \geq \varepsilon_3^*(X)\right). \tag{35}$$

The probabilities given in (28)-(35) are fully determined since $\varepsilon_1, \varepsilon_2, \varepsilon_3$ are assumed to be jointly normal. Given data consisting of G observations $(a_{1g}, a_{2g}, a_{3g}, X_g)$ for $g = 1, ..., G$, the log-likelihood function can then be calculated as

$$\mathcal{L}(\theta; X) = \sum_{g=1}^{G} \ln P^{a_{1g}a_{2g}a_{3g}}(\theta; X_g) \tag{36}$$

where $P^{a_{1g}a_{2g}a_{3g}}(\theta; X_g)$ denotes the probabilities in (28)-(35) evaluated at the point $(a_{1g}, a_{2g}, a_{3g}, X_g)$ for the parameter vector $\theta \equiv (c_0, c_1, \rho)$. The outer loop updates the parameter guess and iterates until convergence using the simulated annealing algorithm.

6.2.3 Comparison of the Two Estimation Strategies

The two estimation procedures have different strengths. The two-step MMSE does not require any parametric assumption on the distribution of private signals. It is also computationally simply. However, the two-step estimator generates less efficient estimates with wide confidence intervals. On the other hand, the Nested Fixed Point method impose joint normality on the private signals. This method is also computationally more costly as it requires both estimating the correlation structure of private signals and solving equilibrium strategies for every set of parameter guesses. But the likelihood objective function in the Nested Fixed Point algorithm is differentiable and converges much faster than the score-type objective function in the two-step method. The standard errors of Nested Fixed Point estimators are also smaller.

6.3 Monte Carlo experiments

In this section, I implement Monte Carlo experiments to explore the finite sample performance of the estimation methods discussed in Section 6.2. Recall that the profit function of each platform i is given by

$$v_i(x) = \begin{cases} c_0 + (c_1 - (\gamma)^{-\alpha})X_i - \sum_{j \neq i} \frac{X_j}{(N-1)(\gamma)^{\alpha}} \mathbb{P}(a_j = 1 | X, \varepsilon_i) + \varepsilon_i & \text{if } a_i = 1 \\ 0 & \text{if } a_i = 0 \end{cases}$$

In this design, I consider three firms ($N = 3$) where the scalar−valued random state variables X_1, X_2 and X_3 are independent of each other. All of them follow a uniform distribution, that is, for $i = 1, 2, 3$

$$X_i \sim U[0, 1].$$

The private shock vector $\varepsilon = (\varepsilon_1, \varepsilon_2, \varepsilon_3)'$ is independent of X and follows a mean-zero multivariate normal distribution with variance $\sigma_i = 1, \forall i = 1, 2, 3$ and correlation coefficient $\rho \in \{0, 0.2, 0.5\}$. The parameters in this model are set as $c_0 = 0$, $c_1 = 2$, $(\gamma)^{-\alpha} = 1$. It can be shown that Assumption 1 - 3 are satisfied under these parameterizations, thus a unique Monotone Pure Strategy Equilibrium exists. For each x, I compute cutoff values $\varepsilon_i^*(x)$ using equation (15). Table 4 show the mean (the top panels) and standard deviation (the bottom panels) of the 2-step MMS and NFXP estimators under different specifications and sample sizes. All results are based on $S = 500$ replications.

Table 4: Finite Sample Performance of Estimators

	$\rho = 0$			$\rho = 0.2$			$\rho = 0.5$		
G	50	100	500	50	100	500	50	100	500
Nested Fixed Point Estimation									
$\hat{c_0}$	0.075	0.079	0.107	0.019	0.005	-0.001	0.006	-0.008	-0.004
	(0.301)	(0.272)	(0.254)	(0.241)	(0.174)	(0.083)	(0.199)	(0.137)	(0.065)
$\hat{c_1}$	1.783	1.738	1.662	1.969	1.978	1.995	2.021	2.007	2.005
	(0.843)	(0.795)	(0.786)	(0.631)	(0.445)	(0.218)	(0.462)	(0.311)	(0.145)
$\hat{\rho}$	0.050	0.034	0.014	0.201	0.197	0.199	0.494	0.498	0.501
	(0.080)	(0.055)	(0.025)	(0.131)	(0.104)	(0.05)	(0.132)	(0.095)	(0.043)
Two-step MMS Estimation									
$\hat{c_0}$	-0.042	-0.042	-0.007	0.090	0.083	0.092	0.069	0.048	0.032
	(0.310)	(0.311)	(0.299)	(0.282)	(0.280)	(0.267)	(0.244)	(0.243)	(0.223)
$\hat{c_1}$	1.535	1.755	1.993	2.009	2.268	2.428	2.022	2.137	2.296
	(1.328)	(1.319)	(1.281)	(1.354)	(1.240)	(1.158)	(1.265)	(1.143)	(1.070)

Results from the Monte Carlo experiment show that the performances of both estimators are robust across different values of correlation coefficient (ρ). The finite sample bias and standard deviation of the estimators both decrease as the sample size increases. The Nested Fixed Point Algorithm yields more efficient estimators than the two-step methods.

7 Empirical Results

In this section, I present the estimation results from applying the two-step MMSE and NFXP methods discussed in Section 6.2 to the censorship data introduced in Section 3. The sample includes 30 events ($G = 30$) and the state variable X is measured by the user share of platforms one week prior to each event using its respective ranking data. Based on the model estimates, I then discuss counterfactual predictions by simulating changes in market structure.

7.1 Parameter Estimates

Table 5 reports parameter estimates from both methods [21]. These estimates are accompanied by bootstrapped 90% confidence intervals. The number of bootstrap replications is 500.

Table 5: Estimation Results on Censorship Data

	$\hat{c_0}$	$\hat{c_1}$	$(\gamma)^{-\alpha}$	$\hat{\rho}$
Two-step MMSE	-1.2563**	2.4322**	1	N/A
	[-1.8995, -0.9665]	[2.0704, 3.1558]	[·]	N/A
Nested Fixed Point Estimation	-0.5060**	1.7139**	1	0.3223**
	[-1.0632, -0.1784]	[1.2388, 2.6376]	[·]	[0.0513 0.6749]

Parameter Interpretations The two estimation methods produce similar point estimates. Estimation results confirm that first, the political cost of non-compliance is positively ($\hat{c_1} > 0$) correlated with a platform's user size. Second, the correlation of platforms' private signals is moderately positive ($\hat{\rho} > 0$). However, the total political pressure is not sufficiently high and is dominated by the combination of economic and strategic incentives ($N\hat{c_0} + \hat{c_1} < \frac{3}{2}(\gamma)^{-\alpha}$). The last result implies that if this market becomes more concentrated, users are not necessarily more likely to experience censorship.

Model Fit Table 6 presents the observed and predicted censorship probability of each platform across the 30 events during 2015-2017. The model fits the level well, indicating that the model is able to recover the market covariates that drive the censorship decisions of platforms in the arrival of an average event in my data.

Table 6: Censorship Probability of Platforms

	Big Platform	Medium Platform	Small Platform
Observed	0.5333	0.2333	0.2333
Predicted (NFXP)	0.5450	0.2324	0.2154

[21] Recall that with MMS estimation, a scale normalization is required and thus I normalize $(\gamma)^{-\alpha} = 1$.

7.2 Counterfactual Predictions

Based on the model estimates, I draw counterfactual predictions from simulating two specific types of government intervention: (i) merging two platforms (ii) permanently shutting down the smallest platform. Let ΔSC denote the percentage change in the scope of censorship if the government were to implement such interventions. Specifically, ΔSC is defined as

$$\Delta SC \equiv [SC_{\text{after intervention}} - SC_{\text{before intervention}}]/SC_{\text{before intervention}}.$$

I assume that the correlation structure of private signals remains the same before and after the intervention. Both counterfactual exercises show that the existence of strategic interaction between platforms mitigates the upward pressure on the scope of censorship that usually follows market concentration.

7.2.1 Merging Two Smaller Platforms

In the Chinese live-streaming market, platforms provide "highly homogeneous products and content" to consumers (China Tech Insights, 2016). One may expect digital platforms to profit from a merger due to the increasing network effect. From the perspective of a regulator, however, is it desirable if the two smallest platforms were to merge? Table 7 reports the results from this counterfactual simulation. We observe that market concentration (via merging two platforms) would lead to a decline in the scope of censorship. This is because although the merged two platforms censor more often than when they were separated due to higher political pressure, the remaining big platform now has stronger strategic incentives to differentiate by not censoring. The latter effect dominates in this case and thus the overall level of compliance in the market is lower following the merger. However, if we ignore the strategic incentives in platforms' decision-making by assuming that users cannot switch between platforms[22], then market concentration would have led to an increase in the scope of censorship.

Table 7: Counterfactual Simulation I (Merging Two Smaller Platforms)

	Two-step MMS Estimation	Nested Fixed Point Estimation
ΔSC	-0.83%	-0.91%
	[-1.36%, -0.30%]	[-1.62%, -0.43%]
ΔSC (without strategic incentive)	1.95%	1.20%
	[0.95%, 2.68%]	[0.60%, 1.85%]

[22]Note that users can still switch to their outside-market options like watching TV or listening music

7.2.2 Permanent Platform Shutdown

Authoritarian regimes are known to shut down a company at will if it does not comply with certain regulations. Then why leave the smallest platform that rarely complies? My simulation results in Table 8 show that permanently shutting down a small platform could backfire and lead to an unintended consequence where the overall censorship is lower in the marketplace.

Table 8: Counterfactual Simulation II (Permanent Shutdown of the Smallest Platform)

	Two-step MMS Estimation	Nested Fixed Point Estimation
ΔSC	-0.57%	-0.89%
	[-1.28%, -0.48%]	[-1.55%, -0.36%]

This is because if the smallest platform is no longer present, the remaining two platforms will share the whole market. They will both obtain stronger strategic incentives to differentiate by not censoring, as they expect to attract more switching users from its now only competitor. When the absence of a non-compliant platform encourages the remaining platforms to comply significantly less often, market concentration turns out pushing down the overall censorship in the marketplace.

8 Concluding Remarks

This paper studies the relationship between online platforms' size, political pressure, and their compliance with censorship regulations. Using panel data on three major live-streaming platforms in China, this paper adopts an event study approach to explore how quickly and intensively platforms censor users' messages following a sequence of unexpected political and social events. The event study analysis shows that the compliance behavior is different across platforms of different sizes: the largest platform not only censored a higher number of keywords on average, it also complied faster than the smaller platforms. While there were no pre-event traffic trends, online traffic significantly declined on all platforms post events, albeit with longer delays for the largest platform.

Motivated by the event-study results, I propose a game-theoretical model of oligopolistic competition. In the model, a platform's profit depends on its own censorship decision as well as that of its competitors, induced by the switching behavior of users with a diverse taste for censorship. The model predicts that if platforms are highly asymmetric, small platforms have strong incentives to differentiate from their big competitors by not censoring, while big platforms find it more costly to delay censorship. However, market concentration comes with two counterveiling forces: first, each platform captures a larger market share and bears higher political costs of non-compliance; second, platforms have more strategic incentives to differentiate from other obedient competitors with non-compliance, now that users have fewer options to switch to. As a result, whether a platform is more or less likely to censor following market concentration depends on which of the two forces dominates. If even a slight increase in a platform's size alarms the government and significantly raises its risk of non-compliance, the former political pressure would dominate and generate more censorship in the marketplace. If, on the other hand, limiting the number of alternatives encourages more users to switch between platforms due to sufficiently lower switching or search cost, then the latter strategic incentive would dominate and cause platforms to censor less often in equilibrium. This paper quantified the relative magnitude of these two forces by exploiting the variation in platforms' market share across different events. Based on the model estimates, this paper simulated two policy-relevant counterfactual experiments. The counterfactual analysis suggests that merging or permanently shutting down small platforms both turn out pushing down the scope of censorship in the marketplace.

My findings indicate that decentralizing online market power may actually help an authoritarian government maintain sufficiently high market-level censorship with minimal enforcement: tolerating a bit of dissent on small platforms allows big platforms to censor more effectively as it mitigates their strategic incentives. In fact, unlike the US market which is dominated by a handful of mainstream social media platforms, Chinese social media is still "very fragmented and localized" (Chiu et al., 2012).

Beyond China, my research also offers some useful insights on regulating misinformation in Western democracies. While most people dislike misinformation and wish it removed, a piece of "fake news" takes time to verify and it sometimes becomes the "alternative truth" among many before it is proven deceptive. When two segments of users co-exist: one is quick to identify "misinformation" and the other takes it as the alternative truth, removing the same piece of content pleases the former at the expense of upsetting the latter. If large platforms are expected to be "more responsible" for removing misinformation or to take actions faster, the latter group may disproportionally switch to small platforms that receive less legal attention every time a piece of misinformation turns viral. Subsequently, social media mergers and acquisitions not only affect the parties involved, but they could also significantly distort other small incumbents' incentives to comply with the regulation

- a distortion that may exacerbate the spread of misinformation and create more "echo chambers" in the long run. Hence policymakers should consider this spillover effect when forming expectations of social media platform's compliance with regulations.

Several limitations remain in this study. First, since I do not observe the actual amount of messages censored by a platform, the number of keywords on a platform's blacklist may not be a perfect indicator for its censorship intensity. For example, some keywords may be used more frequently than others and thus blacklisting a small number of frequently used keywords could affect more users than blacklisting a large number of less common words. Second, this paper is limited to studying only the events that were observed in the two-year dataset of three platforms: there may exist other events that were censored by some other platforms but purposefully ignored by all three platforms. Third, this paper assumes that all users dislike censorship to some extent, but ignores the possibility of users who may be in favor of censorship. In reality, platforms may host both segments of users. All these issues are to be explored in future research.

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Appendices

Proofs

Proof of Theorem 1:

This proof contains two parts: (1) existence of a MPSE and (2) uniqueness of equilibrium.

Existence of equilibrium

First, I prove the existence of a MPSE by extending Lemma 1 in Wan and Xu (2014) to games of N players. First, note that for any $i \in \{1, 2, ..., N\}$ and $(t, x) \in \mathbb{R} \times \Omega_X$, we have

$$\sum_{j \neq i} \delta_j(x)[\frac{\partial \mathbb{P}(\varepsilon_j \geq t|X, \varepsilon_i)}{\partial \varepsilon_i}] = -\sum_{j \neq i} \frac{x_j}{(N-1)(\gamma)^\alpha}[\frac{\partial \mathbb{P}(\varepsilon_j \geq t|X, \varepsilon_i)}{\partial \varepsilon_i}] \tag{37}$$

$$>= -\sum_{j \neq i} x_j \tag{38}$$

$$> -1 \tag{39}$$

where the second last inequality follows Assumption 1. Therefore, $[\sum_{j \neq i} \delta_j(x) \cdot \mathbb{P}(\varepsilon_j \geq t|X, \varepsilon_i) + \varepsilon_i]$ is non-decreasing in ε_i and the single-crossing condition is satisfied. Thus it suffices to show that each firm's interim payoff function is bounded in its type. Since the payoff function is not bounded in my framework, I apply the method proposed in Wan and Xu (2014) to resolve this issue by transforming the payoff function. Let

$$i^*(a_{-i}, a_i, \varepsilon_i) = \begin{cases} -\sum_{j \neq i} \delta_j(x) + \sum_{j \neq i} \delta_j(x) a_j & \text{if } \beta_0 + \beta_1 x_i + \varepsilon_i > -\sum_{j \neq i} \delta_j(x) \\ \beta_0 + \beta_1 x_i + \varepsilon_i + \sum_{j \neq i} \delta_j(x) a_j + \varepsilon_i & \text{if } \sum_{j \neq i} \delta_j(x) \leq \beta_0 + \beta_1 x_i + \varepsilon_i \leq -\sum_{j \neq i} \delta_j(x) \\ \sum_{j \neq i} \delta_j(x) + \sum_{j \neq i} \delta_j(x) a_j & \text{if } \beta_0 + \beta_1 x_i + \varepsilon_i < \sum_{j \neq i} \delta_j(x) \end{cases}$$

be firm i's payoff of choosing $a_i = 1$ relative to that of choosing $a_i = 0$. For any x and ε, each player will make the same choice under the transformed payoff i^* as under the original payoffs. Hence such a payoff transformation does not affect the equilibrium solutions. Now that i^* is bounded, one can verify that all conditions of Athey (2001, Theorem 1) hold and therefore an MPSE exists.

Uniqueness of equilibrium

Given that the equilibrium is monotone, and conditional on $X = x$, platform i is indifferent between censoring or not when the value of its private signal equals to $\varepsilon_i^*(x)$, that is

$$\varepsilon_i^*(x) = -\beta_0 - \beta_1 x_i - \sum_{j \neq i} \delta_j \mathbb{P}(\varepsilon_j \geq \varepsilon_j^*(x)|X = x, \varepsilon_i) \tag{40}$$

Since $\mathbb{P}(\cdot) \in [0,1]$, the cutoff value for each platform is bounded: $\varepsilon_i^* \in [-\beta_0 - \beta_1 x_i, -\beta_0 - \beta_1 x_i - \sum_{j \neq i} \delta_j] \equiv D_i$. Let $D \equiv D_1 \times D_2 \times ... \times D_N$, which is closed and convex. Let Γ denote the response function of each platform such that

$$\Gamma\left(\varepsilon|\beta_0, \beta_1, \{\delta_j\}_{j \in N}, x\right) = \begin{bmatrix} -\beta_0 - \beta_1 x_1 - \sum_{j \neq 1} \delta_j \mathbb{P}(\varepsilon_j \geq \varepsilon_j(x)|X = x, \varepsilon_1) \\ -\beta_0 - \beta_1 x_2 - \sum_{j \neq 2} \delta_j \mathbb{P}(\varepsilon_j \geq \varepsilon_j(x)|X = x, \varepsilon_2) \\ ... \\ -\beta_0 - \beta_1 x_N - \sum_{j \neq N} \delta_j \mathbb{P}(\varepsilon_j \geq \varepsilon_j(x)|X = x, \varepsilon_N) \end{bmatrix}.$$

Clearly, $\varepsilon^* = \Gamma(\varepsilon^*)$ and it suffices to show that $\Gamma(\cdot)$ is a contraction mapping on D. I prove this by showing that the matrix norm of the Jacobian is strictly less than 1, or $||\Gamma'(\varepsilon)||_\infty < 1, \forall \varepsilon \in D$. Formally, we can write out the Jacobian matrix as follows:

$$\Gamma'(\varepsilon) = \begin{bmatrix} \Gamma'_{11} & \Gamma'_{12} & ... & \Gamma'_{1N} \\ \Gamma'_{21} & \Gamma'_{22} & ... & ... \\ \Gamma'_{N1} & ... & ... & \Gamma'_{NN} \end{bmatrix}$$

where

$$\Gamma'_{ij} = -\delta_j \frac{\partial \mathbb{P}(\varepsilon_j \geq \varepsilon_j(x)|X = x, \varepsilon_i)}{\partial \varepsilon_j}, \forall j \neq i$$

and

$$\Gamma'_{ii} = -\sum_{j \neq i} \left(\delta_j \frac{\partial \mathbb{P}(\varepsilon_j \geq \varepsilon_j(x)|X = x, \varepsilon_i)}{\partial \varepsilon_i} \right)$$

Therefore, we have

$$||\Gamma'(\varepsilon)||_\infty = \max_{1 \leq i \leq N} \sum_{j=1}^{N} |\Gamma'_{ij}| \tag{41}$$

$$= \max_{1 \leq i \leq N} \left(|\Gamma'_{ii}| + \sum_{j \neq i}^{N} |\Gamma'_{ij}| \right) \tag{42}$$

$$= \max_{1 \leq i \leq N} \sum_{j \neq i} |\delta_j| \left(\frac{\partial \mathbb{P}(\varepsilon_j \geq \varepsilon_j(x)|X = x, \varepsilon_i)}{\partial \varepsilon_i} + \left| \frac{\partial \mathbb{P}(\varepsilon_j \geq \varepsilon_j(x)|X = x, \varepsilon_i)}{\partial \varepsilon_j} \right| \right) \tag{43}$$

$$\leq \sum_{j \neq i}^{N} x_j \tag{44}$$

$$< 1 \tag{45}$$

where the second last inequality follows Assumption 1. □

Proof of Proposition 1:

We can prove this proposition by applying the implicit function theorem. For any x, the equilibrium probability of platform i is given by $\mathbb{E}(a_i|x) = \mathbb{P}(\varepsilon_i \geq \varepsilon_i^*(x))$. Recall that under Assumption 1, the structural model can be represented by a semi-parametric binary regression model where

$$a_i = \mathbb{1}[\varepsilon_i \geq \varepsilon_i^* = -\beta_0 - \beta_1 x_i - \sum_{j \neq i} \delta_j(x)\sigma_{ij}(x)], \forall i = 1, 2, .., N, \tag{46}$$

where

$$\sigma_{ij}(x) = \mathbb{P}(\varepsilon_j \geq \varepsilon_j^*(x)|X = x, \varepsilon_i = \varepsilon_i^*(x))$$

When competitor platforms are identical, their equilibrium strategies are symmetric such that for any $\forall j, k \neq i$, $\varepsilon_j^* = \varepsilon_k^*$. Each of its competitor platform j owns a mass of $x_j = \frac{1}{N}$ users. Thus the equilibrium cutoff for a platform i is given by

$$\varepsilon_i^* = -c_0 - (c_1 - \gamma^{-\alpha})\left(\frac{1}{N}\right) + \sum_{j \neq i} \frac{\gamma^{-\alpha}}{N(N-1)}\left[1 - \Phi\left(\frac{\varepsilon_j^* - \rho\varepsilon_i^*}{\sqrt{1-\rho^2}}\right)\right]. \tag{47}$$

Taking differences of both sides of equation (47) w.r.t. N, we obtain the following condition:

$$\frac{\Delta\varepsilon_i^*}{\Delta N} = \frac{c_1 - \gamma^{-\alpha}}{N^2} - \frac{\gamma^{-\alpha}}{N^2}\left[1 - \Phi\left(\frac{(1-\rho)\,\varepsilon_i^*}{\sqrt{1-\rho^2}}\right)\right] - \frac{\gamma^{-\alpha}}{N}\phi\left(\frac{(1-\rho)\,\varepsilon_i^*}{\sqrt{1-\rho^2}}\right)\frac{\Delta\varepsilon_i^*}{\Delta N}\left(\sqrt{\frac{1-\rho}{1+\rho}}\right) \tag{48}$$

We can rewrite the above equation as follows:

$$\frac{\Delta\varepsilon_i^*}{\Delta N} = \frac{c_1 - \gamma^{-\alpha}\left[2 - \Phi\left(\frac{(1-\rho)\varepsilon_i^*}{\sqrt{1-\rho^2}}\right)\right]}{N^2 + N\gamma^{-\alpha}\phi\left(\frac{(1-\rho)\varepsilon_i^*}{\sqrt{1-\rho^2}}\right)\left(\sqrt{\frac{1-\rho}{1+\rho}}\right)}. \tag{49}$$

Therefore, $\frac{\Delta\varepsilon_i^*}{\Delta N} > 0$ iff $c_1 > \gamma^{-\alpha}\left[2 - \Phi\left(\frac{(1-\rho)\varepsilon_i^*}{\sqrt{1-\rho^2}}\right)\right]$. We know that $\Phi(\cdot) \in (\frac{1}{2}, 1]$ when $\varepsilon_i^* < 0$, which is equivalent to $c_1 + Nc_0 > \frac{3}{2}\gamma^{-\alpha}$. Hence we have

$$c_1 > \frac{3}{2}\gamma^{-\alpha} \Longrightarrow \frac{\Delta\varepsilon_i^*}{\Delta N} > 0 \Longrightarrow \frac{\Delta\mathbb{P}(\varepsilon_i \geq \varepsilon_i^*(x))}{\Delta N} < 0$$

. □

Proof of Proposition 2:

$$\varepsilon_i^* = -\beta_0 - \beta_1 x_i - \sum_{j \neq i} \delta_j(x)\mathbb{P}(\varepsilon_j \geq \varepsilon_j^*(x)|X = x, \varepsilon_i = \varepsilon_i^*(x)) \tag{50}$$

$$= -\beta_0 - \beta_1 x_i - \sum_{j \neq i} \delta_j(x)\left[1 - \Phi\left(\frac{\varepsilon_j^* - \rho\varepsilon_i^*}{\sqrt{1-\rho^2}}\right)\right] \tag{51}$$

Taking derivatives of both sides of equation (50) w.r.t. ρ, we obtain the following condition:

$$\frac{\partial \varepsilon_i^*}{\partial \rho} = \sum_{j\neq i} \delta_j(x)\phi(\frac{\varepsilon_j^* - \rho\varepsilon_i^*}{\sqrt{1-\rho^2}})[\frac{\frac{\partial \varepsilon_j^*}{\partial \rho} - \frac{\partial \varepsilon_i^*}{\partial \rho}\rho - \varepsilon_i^*}{\sqrt{1-\rho^2}} - \frac{\varepsilon_j^* - \rho\varepsilon_i^*}{2(1-\rho^2)^{3/2}}] \tag{52}$$

In the case of identical platforms, the equilibrium strategies are symmetric and thus $\varepsilon_i^* = \varepsilon_j^*, \forall i, j$. Therefore, we can derive the expression of $\frac{\partial \varepsilon_i^*(x)}{\partial \rho}$ from equation (52). Specifically, for any $1 \leq i \leq N$ and x, we have

$$\frac{\partial \varepsilon_i^*(x)}{\partial \rho} = \frac{D_i}{E_i}.$$

where

$$D_i \equiv -\sum_{j\neq i} \delta_j(x)\phi(\frac{(1-\rho)\varepsilon_i^*}{\sqrt{1-\rho^2}})[\frac{2(1+\rho)+1}{2(1+\rho)\sqrt{1-\rho^2}}]\varepsilon_i^* \tag{53}$$

$$E_i \equiv 1 - \sum_{j\neq i} \delta_j(x)\phi(\frac{(1-\rho)\varepsilon_i^*}{\sqrt{1-\rho^2}})\sqrt{\frac{1-\rho}{1+\rho}} \tag{54}$$

It is easy to see that $E_i > 0$ because the interaction term is always negative $\delta_j(x) < 0$ for any j, x. Therefore

$$sgn(\frac{\partial \varepsilon_i^*(x)}{\partial \rho}) = sgn(D_i) = sgn(\varepsilon_i^*).$$

where $sgn(\cdot)$ is the sign function. Hence the equilibrium probability of platform i declines in ρ if and only if $\varepsilon_i^* > 0$. In other words,

$$\varepsilon_i^* > 0 \iff \frac{\partial \mathbb{E}(a_i|x)}{\partial \rho} = \frac{\mathbb{P}(\varepsilon_i \geq \varepsilon_i^*(x))}{\partial \rho} < 0$$

Next I derive the conditions for model parameters under which $\varepsilon_i^* > 0$. By symmetry, we can obtain the following condition from equation (50):

$$\varepsilon_i^* = -\beta_0 - \beta_1 x_i - [1 - \Phi(\varepsilon_i^*)] \sum_{j\neq i} \delta_j(x) \tag{55}$$

Note that LHS of equation (55) is continuous and monotonically increasing in ε_i^* whereas RHS of equation (55) is continuous and monotonically decreasing in ε_i^*. Hence the solution to equation (55) is unique. As $\varepsilon_i \to -\infty$, $LHS \to -\infty < RHS$; As $\varepsilon_i \to +\infty$, $LHS \to +\infty > RHS$. By intermediate value theorem, $\varepsilon_i^* \in (0, +\infty)$ if and only if $LHS(\varepsilon_i^* = 0) < RHS(\varepsilon_i^* = 0)$, which is equivalent to

$$0 < -\beta_0 - \beta_1 x_i - \frac{1}{2}\sum_{j\neq i} \delta_j(x)$$

Plugging $\beta_0 = c_0$, $\beta_1 = c_1 - (\gamma)^{-\alpha}$, $\delta_j(x) = -\frac{x_j}{(N-1)(\gamma)^\alpha}$ and $x_i = x_j = \frac{1}{N}$ into the above equation, we have

$$0 < -c_0 - \frac{c_1 - (\gamma)^{-\alpha}}{N} + \frac{(\gamma)^{-\alpha}}{2N} \iff (Nc_0 + c_1) < \frac{3}{2}\gamma^{-\alpha}$$

□

Proof of Proposition 3:

I prove this proposition in the following 3 steps.

- Step 1: Show that iff $\beta_1 > 0$, the equilibrium probability of platform i increases in its own size x_i, or equivalently, $\frac{\partial \varepsilon_i^*}{\partial x_i} < 0$.

  Taking derivatives of equation (50) w.r.t. x_i, we obtain

$$\frac{\partial \varepsilon_i^*}{\partial x_i} = -\beta_1 + \sum_{j \neq i} \frac{x_j}{(N-1)\gamma^\alpha} \left(\frac{\partial \mathbb{P}(\varepsilon_j \geq \varepsilon_j^*(x) | X = x, \varepsilon_i = \varepsilon_i^*(x))}{\partial \varepsilon_i^*} \right) \frac{\partial \varepsilon_i^*}{\partial x_i}, \tag{56}$$

  which can be rewritten as

$$\frac{\partial \varepsilon_i^*}{\partial x_i} [1 - \sum_{j \neq i} \frac{x_j}{(N-1)\gamma^\alpha} (\frac{\partial \mathbb{P}(\varepsilon_j \geq \varepsilon_j^*(x) | X = x, \varepsilon_i = \varepsilon_i^*(x))}{\partial \varepsilon_i^*})] = -\beta_1. \tag{57}$$

  By Assumption 1, we know that $\frac{\partial \varepsilon_i^*}{\partial x_i} < 0$ iff $\beta_1 > 0$.

- Step 2: Show that when $\beta_1 > 0$, the equilibrium probability of platform i declines in its competitor's user size x_j, or equivalently, $\frac{\partial \varepsilon_i^*}{\partial x_j} > 0, \forall j \neq i$.

  Taking derivatives of equation (50) w.r.t. x_j, we obtain

$$\frac{\partial \varepsilon_i^*}{\partial x_j} = \sum_{k \neq i} \frac{x_k}{(N-1)\gamma^\alpha} \left(\frac{\partial \mathbb{P}(\varepsilon_k \geq \varepsilon_k^*(x) | X = x, \varepsilon_i = \varepsilon_i^*(x))}{\partial \varepsilon_i^*} \right) \frac{\partial \varepsilon_i^*}{\partial x_j} \tag{58}$$

$$+ \frac{\mathbb{P}(\varepsilon_j \geq \varepsilon_j^*(x) | X = x, \varepsilon_i = \varepsilon_i^*(x))}{(N-1)\gamma^\alpha} + \frac{x_j}{(N-1)\gamma^\alpha} \left(\frac{\partial \mathbb{P}(\varepsilon_j \geq \varepsilon_j^*(x) | X = x, \varepsilon_i = \varepsilon_i^*(x))}{\partial \varepsilon_j^*} \right) \frac{\partial \varepsilon_j^*}{\partial x_j} \tag{59}$$

  which can be rewritten as

$$\frac{\partial \varepsilon_i^*}{\partial x_j} [1 - \sum_{k \neq i} \frac{x_k}{(N-1)\gamma^\alpha} \left(\frac{\partial \mathbb{P}(\varepsilon_k \geq \varepsilon_k^*(x) | X = x, \varepsilon_i = \varepsilon_i^*(x))}{\partial \varepsilon_i^*} \right)] \tag{60}$$

$$= \frac{\mathbb{P}(\varepsilon_j \geq \varepsilon_j^*(x) | X = x, \varepsilon_i = \varepsilon_i^*(x))}{(N-1)\gamma^\alpha} + \frac{x_j}{(N-1)\gamma^\alpha} \underbrace{\left(\frac{\partial \mathbb{P}(\varepsilon_j \geq \varepsilon_j^*(x) | X = x, \varepsilon_i = \varepsilon_i^*(x))}{\partial \varepsilon_j^*} \right)}_{<0} \frac{\partial \varepsilon_j^*}{\partial x_j} \tag{61}$$

By Assumption 1, we know that $\left[1 - \sum_{k\neq i} \frac{x_k}{(N-1)\gamma^\alpha} \left(\frac{\partial \mathbb{P}(\varepsilon_k \geq \varepsilon_k^*(x) | X=x, \varepsilon_i = \varepsilon_i^*(x))}{\partial \varepsilon_i^*} \right) \right]$ on the LHS is positive. From step 1, we know that $\frac{\partial \varepsilon_j^*}{\partial x_j} < 0$ iff $\beta_1 > 0$ and thus both the first and second terms on the RHS are positive. Therefore, it is straightforward to see that $\frac{\partial \varepsilon_i^*}{\partial x_j} > 0, \forall j \neq i$ when $\beta_1 > 0$.

- Step 3: Given Step 1-2, show that a big platform censors more often than a small one. For any two platforms of size $x_1 < x_2$, we can rewrite it as follows

$$x_1 = \frac{1}{2}(x_1 + x_2) - \frac{1}{2}(x_2 - x_1),$$

and

$$x_2 = \frac{1}{2}(x_1 + x_2) + \frac{1}{2}(x_2 - x_1).$$

Let $\varepsilon^*(\frac{1}{2}(x_1 + x_2))$ denote the equilibrium strategy for a platform with user size of $\frac{1}{2}(x_1 + x_2)$. We can thus compare the equilibrium solutions in two markets, one in which there exists two identical platforms 1 and 2 both of size $\frac{1}{2}(x_1 + x_2)$ and the other one in which platform 2 is of larger size x_2 and platform 1 is of smaller size x_1. For firm 2, its own size has increased while its competitor's size has declined in the latter market relative to the former. The reverse is true for firm 1. From Step 1 and 2, we can thus conclude that $\varepsilon^*(x_1) > \varepsilon^*(\frac{1}{2}(x_1 + x_2)) > \varepsilon^*(x_2)$.

□

Proof of Proposition 4:

Let $(x_1, x_2, ..., x_N)$ and $(x'_1, x'_2, ..., x'_N)$ denote the share of platforms ordered by its size in market A and B respectively. I prove this proposition using induction methods. First, I show that when $N = 2$, we have $\mathbb{E}(\sum_{i=1}^2 x'_i a_i | x') < \mathbb{E}(\sum_{i=1}^2 x_i a_i | x)$. Note that $x_1 < x'_1$ and $x_2 > x'_2$ must hold since $HHI_A > HHI_B$. According to Proposition 3, we know that if $c_1 > (\gamma)^{-\alpha}$, then

$$\varepsilon_1^*(x_1, x_2) > \varepsilon_1^*(x'_1, x'_2) > \varepsilon_2^*(x'_1, x'_2) > \varepsilon_2^*(x_1, x_2)$$

Therefore we have

$$\mathbb{E}(a_1|x) = \mathbb{P}(\varepsilon_1 > \varepsilon_1^*(x)) < \mathbb{P}(\varepsilon_1 > \varepsilon_1^*(x')) = \mathbb{E}(a_1|x')$$

and

$$\mathbb{E}(a_2|x) = \mathbb{P}(\varepsilon_2 > \varepsilon_2^*(x)) > \mathbb{P}(\varepsilon_2 > \varepsilon_2^*(x')) = \mathbb{E}(a_2|x')$$

From equation (15), we can write out $(SC_B - SC_A)$ as follows

$$
\begin{aligned}
\mathbb{E}(\sum_{i=1}^{2} x_i' a_i | x') - \mathbb{E}(\sum_{i=1}^{2} x_i a_i | x) &= \sum_{i=1}^{2} (\mathbb{E}(a_i|x') x_i') - \sum_{i=1}^{2} (\mathbb{E}(a_i|x) x_i) \\
&= \mathbb{P}(\varepsilon_1 > \varepsilon_1^*(x')) x_1' - \mathbb{P}(\varepsilon_1 > \varepsilon_1^*(x)) x_1 \\
&+ \mathbb{P}(\varepsilon_2 > \varepsilon_2^*(x')) x_2' - \mathbb{P}(\varepsilon_2 > \varepsilon_2^*(x)) x_2 \\
&= x_1 \Phi\left(-c_0 - \left(c_1 - (\gamma)^{-\alpha}\right) x_1 + x_2 (\gamma)^{-\alpha} \Phi\left(\varepsilon_2^*(x)\right)\right) \\
&- x_1' \Phi\left(-c_0 - \left(c_1 - (\gamma)^{-\alpha}\right) x_1' + x_2' (\gamma)^{-\alpha} \Phi\left(\varepsilon_2^*(x')\right)\right) \\
&+ x_2 \Phi\left(-c_0 - \left(c_1 - (\gamma)^{-\alpha}\right) x_2 + x_1 (\gamma)^{-\alpha} \Phi\left(\varepsilon_1^*(x)\right)\right) \\
&- x_2' \Phi\left(-c_0 - \left(c_1 - (\gamma)^{-\alpha}\right) x_2' + x_1' (\gamma)^{-\alpha} \Phi\left(\varepsilon_1^*(x')\right)\right) \\
&< -\left(x_1' - x_1\right) \Phi\left(\left(c_1 - (\gamma)^{-\alpha}\right)\left(x_1' - x_1\right) + \left(x_2 - x_2'\right)(\gamma)^{-\alpha} \Phi\left(\varepsilon_2^*(x)\right)\right) \\
&+ \left(x_2 - x_2'\right) \Phi\left(\left(c_1 - (\gamma)^{-\alpha}\right)\left(x_2' - x_2\right) + \left(x_1 - x_1'\right)(\gamma)^{-\alpha} \Phi\left(\varepsilon_1^*(x')\right)\right) \\
&< 0,
\end{aligned}
$$

where last inequality follows the fact that $x_2 - x_2' = x_1' - x_1$. Next, assuming that $SC_A > SC_B$ when $N = n$, I show that it is still true in a market with one more platform where $N = n+1$. Let $x_{n+1} = x_{n+1}' = \frac{1}{n+1}$ and scale down the size of remaining platforms by $\frac{1}{n+1}$. It is straightforward to see that in this case, $HHI_A > HHI_B$. Moreover, $\varepsilon_{n+1}^*(x') > \varepsilon_{n+1}^*(x)$. Therefore, we have

$$
\begin{aligned}
\mathbb{E}(x_{n+1}' a_i | x') - \mathbb{E}(x_{n+1} a_i | x) &= \mathbb{P}(\varepsilon_{n+1} > \varepsilon_{n+1}^*(x')) x_{n+1}' - \mathbb{P}(\varepsilon_{n+1} > \varepsilon_{n+1}^*(x)) x_{n+1} \\
&= x_{n+1}\left[\mathbb{P}(\varepsilon_{n+1} > \varepsilon_{n+1}^*(x')) - \mathbb{P}(\varepsilon_{n+1} > \varepsilon_{n+1}^*(x))\right] \\
&< 0.
\end{aligned}
$$

This implies that

$$
\mathbb{E}(\sum_{i=1}^{n} x_i' a_i | x') < \mathbb{E}(\sum_{i=1}^{n} x_i a_i | x) \Longrightarrow \mathbb{E}(\sum_{i=1}^{n+1} x_i' a_i | x') < \mathbb{E}(\sum_{i=1}^{n+1} x_i a_i | x).
$$

Finally, we can conclude that $SC_A > SC_B$ is true for any $N \geq 2$ by induction. □

Proof of Theorem 2:

Suppose that $\mathbb{P}(\varepsilon_{-i} \geq t | X = x, \varepsilon_i)$ is continuous in ε_i. Given that the equilibrium is monotone, and conditional on $X = x$, platform i is indifferent between censoring or not when the value of its private signal equals to $\varepsilon_i^*(x)$, that is

$$
\varepsilon_i^*(x) = -\beta_0 - \beta_1 x_i - \sum_{j \neq i} \delta_j \mathbb{P}(\varepsilon_j \geq \varepsilon_j^*(x) | X = x, \varepsilon_i) \tag{62}
$$

Since the equilibrium is an MPSE, it follows that

$$\begin{aligned} a_i &= \mathbb{1}[\varepsilon_i \geq \varepsilon_i^*(x)] \\ &= \mathbb{1}[\varepsilon_i \geq -\beta_0 - \beta_1 x_i - \sum_{j \neq i} \delta_j \mathbb{P}(\varepsilon_j \geq \varepsilon_j^*(x) | X = x, \varepsilon_i)] \end{aligned}$$

Let $\sigma_{ij}(x) \equiv \mathbb{P}(\varepsilon_j \geq \varepsilon_j^*(x)|X = x, \varepsilon_i = \varepsilon_i^*(x))$. The term $\sigma_{ij}(x)$ should be viewed as an unobservable regressor since ε_i^* is unknown. By Assumption 1, we have

$$\begin{aligned} \sigma_{ij}^0(x) &\equiv \mathbb{P}(\varepsilon_j \geq \varepsilon_j^*(x)|X = x, \varepsilon_i < \varepsilon_i^*(x)) \\ &\leq \mathbb{P}(\varepsilon_j \geq \varepsilon_j^*(x)|X = x, \varepsilon_i = \varepsilon_i^*(x)) \\ &\leq \mathbb{P}(\varepsilon_j \geq \varepsilon_j^*(x)|X = x, \varepsilon_i \geq \varepsilon_i^*(x)) \\ &\equiv \sigma_{ij}^1(x), \end{aligned}$$

and thus

$$\mathbb{1}[\varepsilon_i \geq -\beta_0 - \beta_1 x_i - \sum_{j \neq i} \delta_j(x) \sigma_{ij}^1(x)] \leq a_i \leq \mathbb{1}[\varepsilon_i \geq -\beta_0 - \beta_1 x_i - \sum_{j \neq i} \delta_j(x) \sigma_{ij}^0(x)] \tag{63}$$

□

Proof of Lemma 1:

Let $\delta \equiv \frac{1}{(N-1)(\gamma)^\alpha}$. For arbitrary x,

$$\begin{aligned} \sigma_{ij}^0(X) &= \mathbb{P}\left(\varepsilon_j \geq -\beta_0 - \beta_1 X_j + \sum_{k \neq j} \delta X_k \sigma_{jk}(X) | X = x, a_i = 0\right) \\ &\geq \mathbb{P}\left(\varepsilon_j \geq -\beta_0 - \beta_1 X_j + \delta\left(1 - X_j\right) | X = x, a_i = 0\right) \\ &= \mathbb{P}\left(\varepsilon_j \geq -\beta_0 - \beta_1 X_j + \delta\left(1 - X_j\right) | X = x\right) \end{aligned}$$

and

$$\begin{aligned} \sigma_{ij}^1(X) &= \mathbb{P}\left(\varepsilon_j \geq -\beta_0 - \beta_1 X_j + \sum_{k \neq j} \delta X_k \sigma_{jk}(X) | X = x, a_i = 1\right) \\ &\leq \mathbb{P}\left(\varepsilon_j \geq -\beta_0 - \beta_1 X_j | X = x, a_i = 1\right) \\ &= \mathbb{P}\left(\varepsilon_j \geq -\beta_0 - \beta_1 X_j | X = x\right) \end{aligned}$$

Hence, by the law of iterated expectation,

$$\mathbb{E}\left[\sigma_{ij}^1(X) - \sigma_{ij}^0(X) | X_i = x_i, X_j = t\right] \leq \mathbb{P}\left(-\beta_0 - \beta_1 t + \delta\left(1 - t\right) \geq \varepsilon_j \geq -\beta_0 - \beta_1 t | X_i = x_i, X_j = t\right).$$

For any $\epsilon > 0$, by Chebyshev's inequality we have

$$\begin{aligned}\mathbb{P}\left(\sigma_{ij}^{1}(X) - \sigma_{ij}^{0}(X) \geq \epsilon | X_i = x_i, X_j = t\right) &\leq \frac{\mathbb{E}\left[\sigma_{ij}^{1}(X) - \sigma_{ij}^{0}(X) | X_i = x_i, X_j = t\right]}{\epsilon} \\ &\leq \frac{\mathbb{P}\left(-\beta_0 - \beta_1 t + \delta\left(1 - t\right) \geq \varepsilon_j \geq -\beta_0 - \beta_1 t | X_i = x_i, X_j = t\right)}{\epsilon}\end{aligned}$$

The right hand side converges to 0 as $t \to 1$. $\square$

Event Classification and References

Table 9: Event Classification

Id	Event Name	Event Date	Unexpected	Recurring
1	Tibet Self Immolation	27-May-15	X	
2	DaiJianyong Arrest	28-May-15	X	
3	ZhouYongkang Sentence	11-Jun-15	X	
4	YY adult video	9-Aug-15	X	
5	Tianjin Explosion	12-Aug-15	X	
6	AiWeiWei	13-Aug-15	X	
7	ISIL beheading incidents	18-Aug-15	X	
8	HongKong Election	5-Sep-15	X	
9	Paris Attacks	13-Nov-15	X	
10	Ban of “On the Road”	20-Nov-15	X	
11	HooliganSparrow	22-Jan-16	X	
12	Ezubao	1-Feb-16	X	
13	Oscars2016	28-Feb-16	X	
14	HongKongLocalistLegCoPlans	29-Feb-16	X	
15	Trump Comment on 64	10-Mar-16	X	
16	TianGuo Marching Band	25-Apr-16	X	
17	MiaoDeshun Release	2-May-16	X	
18	Dissident Hunger Strike	4-May-16	X	
19	Jihad Video	22-Jun-16	X	
20	HongKong Booksellers	16-Jun-16	X	
21	WukanMass Protest	19-Jun-16	X	
22	South China Sea	12-Jul-16	X	
23	G20 Summit	4-Sep-16	X	
24	Veteran Petition	28-Feb-17	X	
25	CPPCC national committee	12-Mar-17	X	

Id	Event Name	Event Date	Unexpected	Recurring
26	Xi and Trump Meeting	7-Apr-17	X	
27	Blue Whale Suicide Incidence	9-May-17	X	
28	Uyghurs celebrating Ramadan	26-Jun-17	X	
29	JiangYin Accident	27-Jun-17	X	
30	Carrie Lam	1-Jul-17	X	
31	China’s National Day	1-Oct-49		X
32	Cultural Revolution	16-May-66		X
33	Tiananmen Massacre	4-Jun-89		X
34	FalunGong Movement	20-Jul-99		X
35	16th CPC National Congress	8-Nov-02		X
36	Sichuan Earthquake	12-May-08		X
37	Charter 08	8-Dec-08		X
38	Urumqi Riots	5-Jul-09		X
39	Support Cantonese Movement	25-Jul-10		X
40	Arab Spring	17-Dec-10		X
41	Jasmine Revolution	20-Feb-11		X
42	Wenzhou train crash	23-Jul-11		X
43	Kashgar Riots	28-Feb-12		X
44	Ferrari Crash	18-Mar-12		X
45	18th CPC National Congress	8-Nov-12		X
46	Jingwen Incident	8-May-13		X
47	BoXilai Scandal	22-Sep-13		X
48	Huazang Dharama Sentence	30-Jul-14		X
49	Occupy Movement	28-Sep-14		X

Table 10: Description of events

1 Tibet Self Immolation A mother of two carried out a self-immolation protest in Tibet.

2 Dai Jianyong Arrest A Shanghai artist was detained by Chinese police for “provoking trouble” after he produced a satirical image of President Xi Jinping.

3 ZhouYongkang Sentence As part of President Xi Jinping’s anti-corruption campaign, Zhou Yongkang, who was once one of China’s most powerful political figures, was sentenced to life in prison on corruption charges.

4 YY adult video A performer on YY.com caused a scandal on social media when she accidentally live-streamed herself having sex on the platform.

5 Tianjin Explosion A series of explosions in a container storage station at the Port of Tianjin killed 173 people and injured hundreds of others. This incidence incited criticism about how the government handled the situation.

6 AiWeiWei AiWeiWei, a worldly famous Chinese artist and human rights activist, was given back his passport from the state and came to Munich for medical examinations in August 2015.

7 ISIL Beheading Incidents Khaled al-Asaad was beheaded in Tadmur on August 18, 2015, aged 81, following non-compliance. Al-Asaad was accused by ISIL of being an ”apostate”; the group listed his alleged crimes, including representing Syria at “infidel conferences”, serving as ”the director of idolatry” in Palmyra, visiting Iran and communicating with a brother in the Syrian security services.

8 HongKong Election At least four radical young activists who support greater political autonomy or outright independence from China claimed seats in Hong Kong ’ s 70-member legislative council, or Legco, after a record 2.2 million people went to the polls on September 5, 2015.

9 Paris Attacks The attacks in Paris on the night of Friday 13 November left 130 people dead and hundreds wounded. For Chinese authorities, the Paris attacks proved the dangers of an unrestrained press. The official news agency published an editorial concluding, “there should be limits to free speech.”

10 Ban of "On The Road" A popular online travel show, "On The Road", was banned in China after an episode in which the hosts visited Kurdish fighters in northern Iraq and flew a drone over ISIS filming military positions in neighboring Syria. Media reports claim the show may have been banned over concern that it could invite retaliation from ISIS.

11 Hooligan Sparrow A movie about human rights activist Ye Haiyan, nicknamed "Sparrow" debuted in Sundance Film Festival in January 2016. The movie featured her being chased by local governments and national secret police from town to town.

12 Ezubao Ezubao, a peer-to-peer financial platform based in the eastern Chinese province of Anhui, took in more than 50 billion yuan from 900,000 investors before it came under investigation. It was subsequently shut down and 21 people involved with the scheme were arrested.

13 Oscars2016 Popular online streaming sites abruptly canceled plans to live broadcast the 88th Academy Awards on the eve of the Oscars night in China. Speculations attribute the cancellation to sensitivities cover one of the nominees for Best Documentary Feature, "Winter on Fire", a film on the protests in Ukraine.

14 HongKong LegCo Plans Three localist political Hong Kong groups announced plans for the September 2016 Legislative Council Election.

15 Trump Comment on 64 Donald Trump called the protests in Tiananmen Square a "riot" in a televised debate on March 10, 2016. Trump's comment escalated Chinese routine censorship of all references to Tiananmen or 1989 June 4.

16 TianGuoMarching Band Over 20,000 residents in San Francisco signed petition support for the Tian Guo Marching Band of a Western America Falun Gong-related organization. Falun Gong is a religious group prosecuted by the Chinese communist party.

17 MiaoDeshun Release In May 2016, news reports circulated that Miao Deshun, a man believed to be the last person still in prison for participating in the 1989 Tiananmen protests was scheduled to be released in October 2016.

18 Dissident Hunger Strike A dissident refused to eat in the prison, protesting during the anniversary of the Tiananmen Massacre.

19 Jihad Video Turkestan Islamic Party has an official media center, "Islam Awazi", which translates as the "Voice of Islam". In particular, this online media posted a video titled "My Desire" on July 22, 2016, which highlighted photos of Uyghur fighters in Syria and their struggle with the Chinese army in the city of Urumqi.

20 HongKong Booksellers Lam Wing-kee, one of five Hong Kong booksellers who went missing in 2015 and turned up in mainland custody revealed details of his detention at a press conference in Hong Kong on June 16, 2016.

21 Wukan Mass Protest In 2016, Wukan villagers took to the streets calling for Lin Zulian, a detained democratically-elected local leader and party secretary. They also stroke for the resolution of a long-simmering dispute over land sales.

22 South China Sea Disputes On July 12, 2016, an international tribunal in the Hague ruled in favor of the Philippines and concluded that China has no legal basis to claim historic rights in the South China Sea. Within hours of the announcement, "South China Sea arbitration" was trending on Weibo, and hundreds of thousands of comments poured in. A wave of censorship accompanied this outpouring of online commentary, targeting extreme comments that call for war.

23 G20 Summit In the 11th meeting of the G20, President Xi Jinping made a gaffe accidentally saying "facilitate commerce, and loosen clothing" when he should have said "facilitate commerce and be lenient to farmers".

24 Veteran Petition On February 22, 2017, hundreds of protesters, dressed in green and blue camouflage fatigues, gathered on Wednesday morning outside the Communist Party ’ s anti-corruption agency. They demanded unpaid retirement benefits in a new wave of protests highlighting the difficulty in managing demobilized troops.

25 CPPCC national committee On March 12, 2017, Xi Jinping and Li Keqiang listened to the CPPCC national committee report, the two continued to talk to discuss and interact frequently. Outsiders hold the view that the meeting of Chinese top political leaders as unusual political signals.

26 Xi and Trump Meeting Trump and Xi Jinping met at Sea Lake Manor (Mar-a-Lago) in Palm Beach, Florida on Thursday night (April 7). This was the first time the two world leaders met.

27 Blue Whale Suicide Incident The online suicide game "Blue Whale" targeting teenagers and young children triggered panic among parents and authorities in China after an incident on May 9, 2017.

28 Uyghurs Celebrating Ramadan Chinese officials are trying to prevent people from fasting during Ramadan in the predominantly Muslim province of Xinjiang. According to the World Uyghur Congress (WUC), officials in the region ordered all restaurants to remain open and a series of measures have been put in place seemingly designed to prevent people from observing the holy month.

29 Jiangyin Accident Two men and one woman stabbed to death in Jiangyin, Wuxi, a town in east China.

30 Carrie Lam In the 2017 Chief Executive election, Lam won the three-way election with 777 votes of the 1,194-member Election Committee as the Beijing-favoured candidate, beating former Financial Secretary John Tsang and retired judge Woo Kwok-hing, becoming the first female Chief Executive of Hong Kong. She assumed office on July 1, 2017.

31 China's National Day Criticism or grievance about the communist party usually crop up when the parade airs on TV celebrating the forming of the Central People's Government of China taking place in Tiananmen Square on October 1.

32 Cultural Revolution On May 16, 1966, a notification was published by the Communist Party of China that described Mao's ideological justification for the Cultural Revolution. Opinions over the legacy of the revolution remain divided.

33 Tiananmen Massacre The Tiananmen Square protests were student-led demonstrations in Beijing in 1989. The protests were forcibly suppressed after the government declared martial law.

34 FalunGong Movement Falun Gong is a religious movement in China that has been officially persecuted by the government on 20 July 1999.

35 Sichuan Earthquake After an earthquake hit the Chinese province of Sichuan on May 12, 2008, there was a series of allegations of corruption against officials involved in the construction of schools in regions affected by the earthquake. Postings about the scandal flooded Chinese online portals.

36 16th CPC National Congress The 16th National Congress of the CPC was held on November 8, 2002, in Beijing. The Congress marked the transition of power between Jiang Zemin and Hu Jintao.

37 Charter 08 Charter 08 is a manifesto initially signed by over 350 Chinese intellectuals and human rights activists. The Charter calls for 19 changes including an independent legal system, freedom of association and the elimination of one-party rule.

38 Urumqi Riots The July 2009 Urumqi riots were a series of violent riots among Uyghurs and Han Chinese people that broke out on 5 July 2009 and lasted for several days in Urumqi, China.

39 Support Cantonese Movement Government officials in Guangdong, a southern Chinese province, announced that they planned to switch the language of most of its TV programs from Cantonese to Mandarin on September 1, 2015. The news led to a round of criticism among Cantonese speakers in Guangzhou city.

40 Arab Spring The Arab Spring was a series of anti-government protests, uprisings and armed rebellions that spread across the Middle East in early 2011. These events led to wide discussions among the netizens in China.

41 Jasmine Revolution The "Chinese Jasmine Revolution" refers to the Chinese pro-democracy protests with public assemblies in over a dozen cities in China starting on 20 February 2011, inspired by and named after the Jasmine Revolution in Tunisia.

42 Wenzhou Train Crash On July 23, 2011, two high-speed trains traveling on the railway line collided on a viaduct in the suburbs of Wenzhou, China. Officials responded to the accident by hastily concluding rescue operations and ordering the burial of the derailed cars. These actions elicited strong criticism from Chinese media and online communities.

43 Kashgar Riots In February 2012, 12 people died in riots near the north-western city of Kashgar in Xinjiang province.

44 Jingwen Incident In May 2013, police ruled suicide for a woman who fell from a building, while family organized thousands of people in a march to ask for an investigation.

45 BoXilai Scandal Bo Xilai, a former senior Chinese politician, was found guilty of corruption, stripped of all his assets, and sentenced to life imprisonment on 22 September 2013.

46 Ferrari Crash In March 2012, there was a fatal car crash involving a Ferrari, that was driven by the son of party official close to President Hu Jintao. Within hours of the crash, photos were deleted off the Internet and searches of "Ferrari" were blocked.

47 HuazangDharama Sentence Chinese authorities accuse Wu Zeheng, the head of the Buddhist-inspired Hua Zang Dharma, of using his holy status to defraud and have sex with devotees. This prosecution has been called politically motivated.

48 18th CPC National Congress The 18th National Congress of the Communist Party of China began on November 8, 2012, in Beijing, China. The Congress marked the transition of power between Chinese former President Hu Jintao and President Xi Jinping.

49 Occupy Movement Occupy movement is an international socio-political movement against social inequality and a lack of "real democracy" around the world, its primary goal being to advance social and economic justice and new forms of democracy.

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