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. Based on 30 unexpected sensitive events, I first present reduced form evidence that the largest platform censored a higher number of keywords and complied faster on average than the smaller platforms. I then develop and estimate a structural model where platforms compete for users by choosing whether to comply with the government's censorship requests. By complying immediately, platforms may lose users who prefer to evade censorship by switching out. By delaying compliance, 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 obey the government's censorship requests. My counterfactual analysis predicts that centralizing market power via merging or shutting down small platforms could backfire and the overall censorship turns out to be lower.

Keywords : Censorship, strategic interaction, market concentration

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1 Introduction

On August 12, 2015, a series of massive explosions occurred in the city of Tianjin in northeast China. According to a BBC report[1], over 100 people were killed and nearly 800 others were injured. Shortly thereafter, the public started to speculate over the cause of this event. Some rumors circulated that an overheated chemical warehouse, which had operated illegally for years because of its owner's strong political ties with the government, was the culprit of this disastrous event. After the blasts, local residents seeking compensation for their homes protested in front of the venue of the daily press conference.[2] During the protest, the Chinese government disseminated urgent albeit vague guidelines to social media platforms, requesting them to censor online discussions on the Tianjin Explosion.[3] Some social media platforms complied immediately by censoring user messages that contained keywords such as "Tianjin massive explosion" via implementing a method called "automated keyword filtering." Some other platforms, however, did not comply immediately despite the potential risk of penalization from the Chinese government. In fact, social media companies in China "appear to have a degree of flexibility in determining when and what specific keywords to block" (Knockel, 2016) −the decision of whether to comply is not as simple as it may seem on the surface.

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 little 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. For example, Facebook was criticized by the Ministry of Justice in Germany for having deleted only 39% of the hate-

[1] Source: https://www.bbc.com/news/world-asia-china-33844084
[2] Source: https://www.theatlantic.com/international/archive/2015/08/chinas-response-tianjin-explosions/401426/
[3] Source: https://www.wsj.com/articles/BL-CJB-27514

speech 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). In the United States, following Twitter's placement of warning labels on controversial tweets from former US President Donald Trump, some Republicans flocked to a new social media platform, Parler, that has dubbed itself a "pro-free speech" alternative (Brewster, 2020). If the implementation of a regulation creates a significant competitive disadvantage for a firm, the firm may have an incentive to minimize the impact of this regulation by delaying its compliance or not complying at all. How does competition affect such incentives of a firm, and consequently the market-level compliance?

This paper studies these questions through a unique empirical 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. This 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 sensitive events during the data collection period, such as the 2015 Tianjin Explosion mentioned above, 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 the 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 using 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 during most events.

Motivated by this empirical pattern, I develop 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 the number of users, who have heterogeneous preferences for censorship. Hence, platforms can use their decisions on censoring to compete for users. For each unexpected sensitive event, online platforms receive requests for censoring a set of keywords related to these events and decide simultaneously whether to comply immediately. Users obtain disutility[4] from being censored and may evade censorship by switching to another platform which incurs a fixed switching cost. On the one hand, platforms are under political 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 could 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, consolidating market power via merging or shutting down small platforms does not necessarily cause more censorship in the marketplace.

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 depends on which of the two forces dominates. If even a slight increase in a platform's size alarms the government and significantly increases the platform's political cost 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

[4] In my framework, the social media platform serves two purposes: first, as an information channel, and second, an discussion or engagement facilitator. The censorship typically happens after an event with a time lag, therefore it would not prevent the information dissemination, but it would prohibit further discussions of the event on the platform, therefore creating a disutility for its users. The author is grateful to Ying Xie for pointing this out.

counterfactual analysis shows that shutting down a small platform with the goal of censoring users could backfire and lead to an unintended consequence where the overall censorship turns out to be lower.

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 Russia 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. This might be one of the reasons why, unlike the US market dominated by a handful of mainstream social media platforms, Chinese social media remains "very fragmented and localized (Chiu et al., 2012)."

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 presents the estimation results. Section 7 provides policy-relevant 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 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 the majority of 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 of selectively filtering information, it is different from the above-mentioned research by focusing on the timing of content moderation, instead of the content itself.

This paper also draws from and contributes to empirical work on the discrete choice models of firms' strategic 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. (2016);Qin et al. (2018); Hobbs and Roberts (2018); Chen and Yang (2019)). Most existing papers either empirically examine the nature of censored content and how social media users responded to the act of censorship, 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.

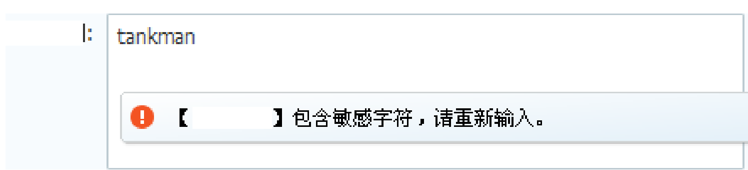
3 Data and Institutional Background

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.[5] Researchers from the Citizen Lab decrypted the entire blacklists of keywords using several reverse engineering techniques (Knockel et al., 2015). By using tools for finding cryptographic constants inside a program's address space as it is running, they identified the files that stored blacklisted keywords and the URLs from which keywords updates were downloaded for three most popular live-streaming platforms in China: YY, 9158 and Sinashow.[6] These built-in lists of keywords perform checks to determine whether 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[7] 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 screenshot of blacklisted keyword that triggers censorship on YY.



Notes to Figure 1. The text following the warning sign is translated as "[The message you sent] contains sensitive words. Please try again."

To uncover the complete history of censorship, the Citizen Lab performed an hourly download and decrypted all three platforms' keyword blacklists between February 2015 to August 2017. A total of 18,655 unique keywords[8] were uncovered from the blacklists of all

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

[6]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).

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

[8]including phone numbers and URLs.

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 six general themes according to a codebook developed in Crandall et al. (2013). Table 1 provides some example categories of keywords grouped into each theme. The blacklisted keywords target a variety of content including issues related to sensitive events, Chinese politics, circumvention tools, pornography, gambling, and illicit drugs. Notably, the Chinese government is most likely to surveil the platforms for compliance of censorship during critical times when information has the greatest impact, such as during elections, periods of civil unrest, and sensitive political anniversaries (Crandall et al., 2013). My study thus focuses only on the keywords grouped into the "event" category. 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. Keywords in the "event" 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 8 and Table 9) provides a detailed description on and reference links to all the events included in this study. Based on the event dates, I separate these events into two distinct groups: unexpected and recurring events[9].

[9] Knockel et al. (2015) included a subset of the events studied in this paper. My classification rule for the events are slightly different from theirs. They separated the events into three categories: scheduled events, recurring events, and current events. The former two corresponds to the "recurring events" and the last one the "unexpected events" based on my definition.

Table 1: Content Themes and Related Categories of Blacklisted Keywords

Theme	Example categories	Example translations and original keywords
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)

Notes to Table 1. Based on the contextual information, three researchers from the Citizen Lab coded each blacklisted keyword into one of 80 content categories grouped under six general themes according to a codebook. This table listed some keywords (in parentheses) and their translations in some example categories from each of the six themes. In the Chinese language, words are concatenated together whereas English words are separated by whitespace or punctuation. In other words, the original keywords on the blacklists convey information much the same way as English phrases do.

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. In the empirical analysis, I will mainly focus on the the "unexpected" events for two reasons: (1) as both users and platforms could anticipate the (anniversary) date of recurring events, chances are that users start engaging in event-related conversations days prior to the event date and thus platforms may need to add related keywords preemptively; (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.

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. Specifically, 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, in the data, there is only a small fraction ($< 0.5\%$) of keywords that 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.

I developed a secondary dataset by scraping each platform's daily traffic from Siterank-data.com. This data source provides the history of websites' global traffic ranks reported by Alexa[10] 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[11]. Specifically, the higher a platform's rank (i.e. smaller rank number) is, the more popular it is 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 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 the three platforms and their estimated daily unique visitors.

[10] https://www.alexa.com

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

Table 2: Summary Statistics on Platform Daily Alexa Ranks

Platform	Daily Alexa Rank				Daily Unique Visitors (est.)	
	Mean	Std. Dev	Min	Max	Mean	Std. Dev.
YY	7,889	3,091	3,838	16,324	6,417,513	3,143,050
9158	84,428	21,674	49,687	183,707	168,088	54,944
Sina Show	1,006,252	984,578	26,763	4,389,840	5,052	1,035

Notes to Table 2. The summary statistics are calculated based on the daily Alexa ranking data between July 5, 2015 and August 15, 2017. The last two columns refer to the estimated daily unique visitors of each platform based on their daily Alexa ranking data and bi-monthly reported daily unique visitors. To minimize the effect of measurement error, this paper only uses the daily Alexa rank as a proxy for the platform traffic.

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 two main 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 occurrence of unexpected politically sensitive events. This makes it empirically possible to study platforms' interaction and detect potential strategic responses.

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, developed by YY Inc, is the largest live-broadcasting platform in China during the data collection period in terms of its user population. Tian Ge Interactive Holdings Limited owns two other platforms: 9158 and Sina Show. Not only did YY and Tian Ge list each other as close competitors on their websites for investors, but they were also both market leaders: by revenue, YY owns a share of 40% and Tian Ge 28% in 2015.[12] In addition, approximately 9% of 9158 users are active on both platforms: 9158 and YY.[13] This shows that the proportion of multi-homing users is limited and most users in the market use only one platform at a time. Although both Sina Show and 9158 are listed under the same parent company Tian Ge, they are operated by two different subsidiary companies with separate administrative teams: 9158 was founded in 2008 by Jinhua Jiuyuewoba Network Technology Co., Ltd with a registered capital of RMB 10 million, whereas Sina Show separated from Sina UC and registered itself under Xinxiu Dongli Culture Media Co., Ltd in 2010.[14] Moreover, the two platforms do not use the same blacklist of keywords and the Jaccard similarity coefficient[15] between the blacklists of Sina Show and 9158 is less than 0.4 (Knockel et al., 2015).

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. Figure 6 in Appendix shows the screenshot of user interface on one of the platforms in this study. Their major source of revenue includes monetizing through user tips and 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 (Geron, 2012). Since these platforms profit from active user engagement

[12] See statistics from "Corporate Presentation of YY Inc. July 2015."
[13] See statistics from qianfan.analysis.cn.
[14] Source: https://www.qcc.com
[15] The Jaccard similarity coefficient measures similarity between finite sample sets, and is defined as the size of the intersection divided by the size of the union of the sample sets.

on a daily basis, censorship disrupts online user activity and thus incurs significant cost to the platforms.

To simplify the notation, I will refer to YY, 9158, and Sina Show as the big, medium, and small platforms respectively in all subsequent sections.

4 Event Study Analysis

In general, there are many internal and external factors that could trigger a platform's censorship decision: a surge in the number of users (and thus higher probability of witnessing sensitive content), the preference of a platform owner, requests from local governments, 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. Therefore, I adopt an event-study approach to analyze how a platform's censorship intensity, measured by the number of blacklisted keywords associated with an event, dynamically changes as the event unfolds. Due to the reasons mentioned in Section 3.1, I will focus only on the "unexpected events" to minimize confounding effects. The event-study results show that the big platform censors more keywords and also responds faster than the medium and small platforms on average. All the platforms experienced a significant decline in its post-event traffic.

4.1 Platform 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 $i(= Big, Medium, Small)$ on calendar day d, ϕ_q is a seasonal (quarter) 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_t^i represents the time trend of platform i's censorship intensity (i.e. number of keywords censored) relative to the event dates, conditional on seasonal and event fixed effects. Formally, we write:

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

where $\mathbb{1}[.]$ is an indicator function that takes value of 1 if the expression in brackets is true and 0 if otherwise; t_e is the date when an event $e \in \{E_1, E_2, ..., E_{30}\}$ occurred. Figure 2 provides a visual representation of how the event-time dummy variables are constructed relative to the calendar dates.

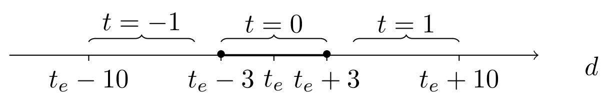


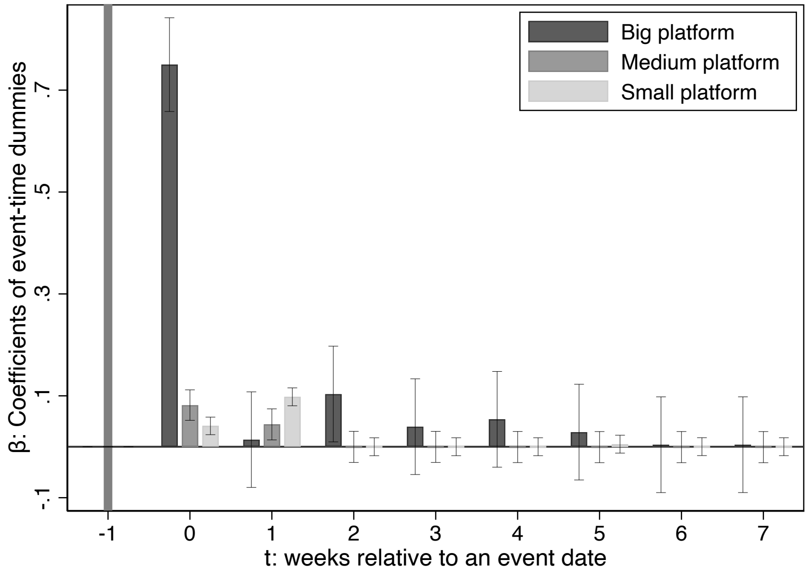
Figure 2: An illustration on how the event-time dummy variables are constructed

It is well-known that not all βs can be identified in this case because 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:

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

This 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. Figure 3 plots the estimated censorship coefficients (β_t^i) for all three platforms.

Figure 3: Coefficient plot of event-time dummies in regression (1)



Notes to Figure 3. This figure plots the estimated coefficients ($\beta_t^i, t = 0, 1, ..., 7$) of the (post-event) event-time dummies for all three platforms ($i = Big, Medium, Small$) in regression (1). Since none of the three platforms added any keywords associated with any unexpected event before it occurred, I omitted the coefficient plots for all the β_i^ts where $t < 0$.

4.2 Platform Traffic

In order to study the time trend of platforms' traffic 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 econometric model

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

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

$$H_0 : b_t^i = 0, \forall t < 0, i = Big, Medium, Small.$$

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 by constructing

F statistics with robust standard errors clustered at the event level. Table 3 reports the

Table 3: Joint test statistics of pre-event coefficients

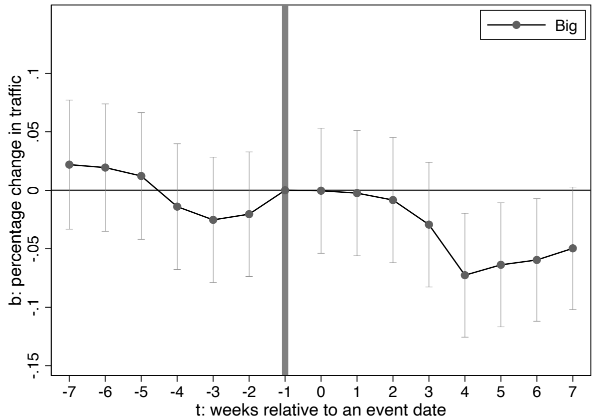
Platform i	Null Hypothesis	F statistics	p-value
Big	$b^B_{-1} = b^B_{-2} = ... = b^B_{-7} = 0$	0.86	0.5414
Medium	$b^M_{-1} = b^M_{-2} = ... = b^M_{-7} = 0$	1.02	0.4154
Small	$b^S_{-1} = b^S_{-2} = ... = b^S_{-7} = 0$	0.64	0.7201

test statistics for the joint significance 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 shows that the event classification scheme mentioned in Section 3.1 provides relatively accurate information about the dates and nature of unexpected events. Figure 4 plots the estimated traffic coefficients (b^i_t) from regression (2) for the (a) big, (b) medium, and (c) small platforms respectively.

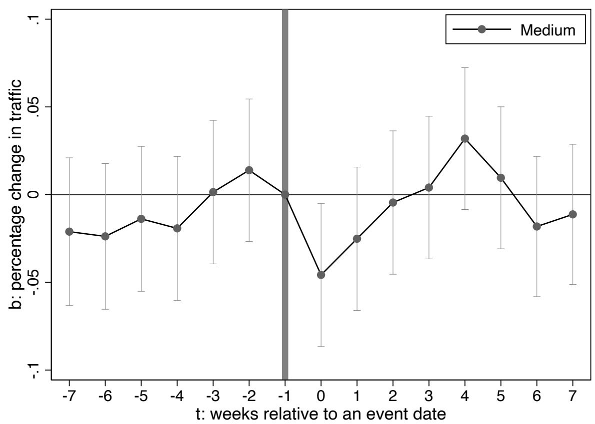
4.3 Event Study Results

The event study results on the censorship behavior (Figure 3) and traffic (Figure 4) of platforms revealed three facts. First, the big platform censored on average more keywords and also reacted faster than the medium and small platforms (i.e. $\beta^0_B > \beta^0_M > \beta^0_S > 0$). On the other hand, the small platform tends to delay censoring most of its keywords by a week compared to the medium and big platforms (i.e. $\beta^1_S > \beta^1_M > \beta^1_B > 0$). 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% within the event week, while the big platform's traffic began to show a decline on average 4 weeks after event occurrence. On the other hand, the small platform lost almost 50% of its users around two weeks after an event occurred. This drastic change in the traffic of small platforms is likely caused by the noise of Alexa ranks for small sites. This is because a very small change in the number of visitors to a small site usually leads to a large change in its rank. Third, traffic on all platforms eventually reverted back to the pre-event level approximately 5-7 weeks after the

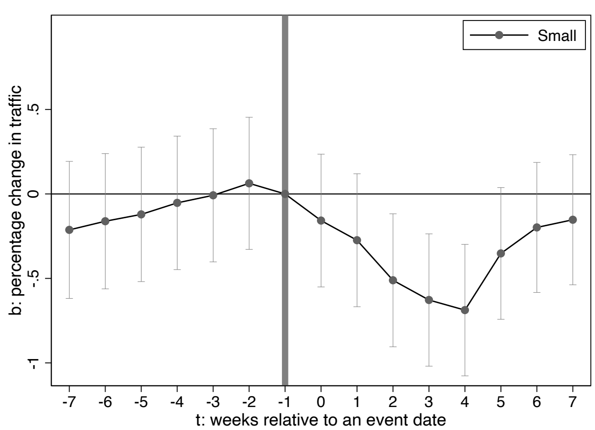
Figure 4: Coefficient plots of event-time dummies in regression (2)



(a) Big Platform (YY)



(b) Medium Platform (9158)



(c) Small Platform (Sina Show)

Notes to Figure 4. The three panels in this figure plot the estimated coefficients (b_t^i) of the event-time dummies in regression (2) for each platform ($i = Big, Medium, Small$) respectively. Since the dependent variable is a proxy of the log of user size, the coefficient of each event-time dummy represents the percentage change in traffic of the platform in that particular week relative to the platform's traffic one week before the event date.

event outbreak.

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 or not to add keywords within one week of event occurrence.[16] Hence platform i has a decision variable $a_i \in \{0, 1\}$ denoting its decision to censor (1) or not (0). Platforms 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 thus refer to them as the "captive users." This assumption is motivated by the event-study results in Figure 4: all platforms' traffic eventually reverts back to the pre-event level approximately 5-7 weeks after the event dates. In other words, switching is temporary because users typically switch out either to seek out further information or to engage in time-sensitive discussions about an event. As an event becomes less news-worthy over time, due to network effect, captive users tend to return to their favorite and most familiar platforms for entertainment activities.

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

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 users" of platform i. c_0 can be viewed as a fixed penalty from non-compliance, while c_1 is the expected loss per user from a temporary shutdown by the government due to non-compliance. ε_i is the private signal observed only by platform i. However, private signals are allowed to be correlated across platforms and the joint distribution of these private signals are assumed 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 receive private information of censorship guidelines from different "resources distributed across several bureaucracies" (Miller, 2017). These guidelines, to the platforms' 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.[17] 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[18] with a shape parameter denoted by $\alpha(> 0)$ and its location parameter

[17]The single-homing assumption is based on the fact that less than .9% of the users have accounts of both YY (big platform) and 9158 (medium platform) according to the 2015 annual report from Analysis.cn.

[18]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 model tractability,

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 do 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.[19] 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 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 $\underline{\theta_i}(a)$ 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

I assume that θ is drawn from a Pareto distribution as it is scale-free and associated with a simple CDF.

[19] I refer to these "outside options" as any form of leisure activities that users may adopt after they give up seeking information or discussing about the sensitive events online.

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 when $a_i = 1$ in equation (5), 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 and its rivals choices $\{a_j\}_{j \neq i}$, platform i's (realized) payoff when censoring relative to not censoring can be expressed as follows,

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

where

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

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

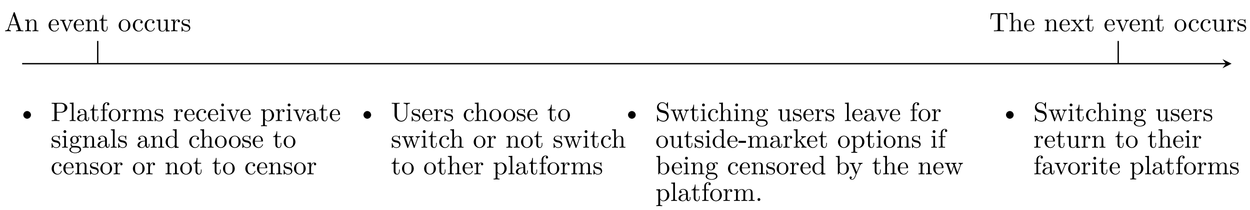
$$\delta = -\frac{1}{(N-1)(\gamma)^{\alpha}}. \tag{11}$$

Since platform i will choose $a_i = 1$ if and only if equation (8) is positive, we can rewrite the profit function of platform i into the following relative form:

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

Note that equation (12) corresponds to the reduced-form profit function widely adopted in the literature on social interactions (e.g. Bajari et al. (2006); De Paula and Tang (2012); Aradillas-Lopez and Gandhi (2013)), and (δx_j) is referred to as the "strategic interaction" term. In my framework, this term maps to a function of platforms' user size scaled by some structural parameters. Since $\delta x_j < 0$ 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 the two parameters, the more likely a bigger proportion of users would switch to a competitor platform that does not censor, which implies that a platform's choice of censorship becomes more sensitive to its competitors' actions. Figure 5 summarizes the timing of the game.

Figure 5: Timing of the game



5.3 Bayesian Nash Equilibrium Strategies

Without loss of generality, this paper assumes that the outcome observed is the result of a pure strategy[20] Bayesian Nash Equilibrium (BNE). 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 is greater than if it chooses action 0, i.e.,

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

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[21] 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*

[20] 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.

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

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,

$$\varepsilon_i^*(x) = -\underbrace{\left[c_0 + (c_1 - (\gamma)^{-\alpha})x_i\right]}_{\text{political cost (net of economic gains)}} + \underbrace{\sum_{j \neq i} \frac{x_j}{(N-1)(\gamma)^{\alpha}} \mathbb{P}\left[\varepsilon_j \geq \varepsilon_j^*(x) | \varepsilon_i = \varepsilon_i^*(x)\right]}_{\text{strategic incentive}} \tag{15}$$

Let $\mathbb{P}(\varepsilon_i \geq \varepsilon_i^*(x))$ denote the equilibrium probability of censorship for platform i. Note that the first two terms in bracket on the right hand side of equation (15) correspond respectively to the expected *political cost* $(c_0 + c_1 x_i)$ and the expected *economic gains* $(x_i \gamma^{-\alpha})$ for platform i if it does not comply to censor (i.e. $a_i = 0$); The economic gains refer to the amount of users platform i would manage to keep relative to the case where the platform complies to censor $(a_i = 1)$. The third term of equation (15) stands for the expected *strategic incentives* between competitor platforms discussed before. The strategic incentive stems from the expected traffic brought about by potential switching users from other platforms.

From equation (15), we know that each platform's equilibrium strategy varies with respect to market covariates. However, upstream agents, such as an anti-trust regulator or an authoritarian government, are in general more concerned about the overall compliance level in the market and how it affects an average user as opposed to that of a particular platform.

Then, how will the overall level of compliance (censorship) change as a result of a more concentrated or decentralized marketplace?

If a market becomes more concentrated by hosting fewer platforms, two factors will be at play: first, each platform captures a larger market share and bears higher political costs of non-compliance; second, each platform is also subject to higher 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 a salient event depends on which of the above two forces dominates. If even a slight increase in the platforms' sizes alarms the government and significantly increases the risk of non-compliance, the former political cost would dominate and lead to 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 estimating the model with the data described in Section 3. Specifically, I define an index to measure the market-level compliance, which I refer to as the "scope of censorship" (SC). In a market of N platforms, the index is defined as below:

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

In other words, SC equals the expected share of platform users in the market affected by censorship during a salient event.

6 Model Estimation

This section discusses the empirical strategies of identifying and estimating the model. I also illustrate the estimators' finite sample performance through a Monte Carlo experiment in the Appendix. In particular, I consider each event in the data as an independent game and assume that the structural parameters in my model remain the same across different games. Since the live-streaming platforms I study share very similar business models and offer almost identical (entertainment) services to their users, I consider the platforms as non-differentiated except for their market share. In other words, I assume that other factors that may have differentiated the platforms are orthogonal to platforms' censorship decisions. 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 costs 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 identification strategy is conditional on the existence of exclusion restriction in this model: changes in the traffic of a competitor platform only affect 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. Finally, I present the estimation results and discuss their implications.

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 model parameters $(c_0, c_1, (\gamma)^{-\alpha})$ are 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*

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

and

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

where

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

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

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[22].

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

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

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. $\beta_1 = c_1 - \gamma^{-\alpha} \neq 0$. *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 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

[22]Moreover, they collapse to be the same, 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 $i \neq j$.

(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 $(\gamma)^{-\alpha}$ to 1.

6.2 Estimation Methods

In this section, I begin by presenting two different estimation procedures and then discuss their respective strengths and weaknesses.

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 1-3 are satisfied and let $\theta_0 \equiv (c_0, c_1)$, then

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

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

$$\begin{aligned}\xi_i = {} & g_i(X) sgn\left[c_0 + (c_1 - 1)X_i - \sum_{j \neq i} \left(\frac{1}{N-1}\right) X_j \sigma_{ij}^0(X)\right] \\ & + (1 - g_i(X)) sgn\left[c_0 + (c_1 - 1)X_i - \sum_{j \neq i} \left(\frac{1}{N-1}\right) X_j \sigma_{ij}^1(X)\right],\end{aligned} \tag{22}$$

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

$$\hat{\theta} = \arg\max_{\theta \in \Theta} \mathcal{U}_G \left(\theta; \hat{\xi}, \hat{\sigma}\right), \tag{23}$$

where

$$\mathcal{U}_G \left(\theta; \hat{g}, \hat{\sigma}\right) = \frac{1}{G\left(G-1\right)} \sum_{k=1}^{G} \sum_{l \neq k}^{G} \sum_{i=1}^{N} \left\{\left(2a_{il} - 1\right) K_h \left(X_l - X_k\right) \xi_i \left(x\right)\right\}. \tag{24}$$

Here G is the number of games and $K_h\left(\cdot\right) = K\left(\cdot/h\right)/h^d$ is a kernel function with smoothing bandwidth h. However, $\mathcal{U}_G\left(\theta; \hat{g}, \hat{\sigma}\right)$ is an infeasible sample analog because $\sigma_{ij}^0, \sigma_{ij}^1$ and g_i are unknown. To resolve this issue, I plug their non-parametric estimates $\hat{\sigma}_{ij}^0, \hat{\sigma}_{ij}^1$ and $\hat{g}_i$ respectively into equations (22) and (24). First, I estimate $\hat{\sigma}_{ij}^0$ and $\hat{\sigma}_{ij}^1$ by

$$\hat{\sigma}_{ij}^0(x_k) = \frac{\sum_{l \neq k}^{G} a_{jl} a_{il} K_h\left(X_l - x_k\right)}{\sum_{l \neq k}^{G} \left(1 - a_{il}\right) K_h\left(X_l - x_k\right)} + G^{-\frac{1}{2}}, \tag{25}$$

$$\hat{\sigma}_{ij}^1(x_k) = \frac{\sum_{l \neq k}^{G} a_{jl} a_{il} K_h\left(X_l - x_k\right)}{\sum_{l \neq k}^{G} a_{il} K_h\left(X_l - x_k\right)} - G^{-\frac{1}{2}}, \tag{26}$$

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 the inequality $\hat{\sigma}_{ij}^0(x) \leq \sigma_{ij}^0(x) \leq \sigma_{ij}^1(x) \leq \hat{\sigma}_{ij}^1(x)$ holds with probability approaching one (faster than any polynomial rates). Then I estimate $g_i(x)$ by

$$\hat{g}_i(x_k) = \mathbb{1}\left[\frac{1}{\left(G-1\right)} \sum_{l \neq k}^{G} \left\{2a_{il} - 1\right\} \times K_h\left(X_l - x_k\right) \geq 0\right] \tag{27}$$

The first stage nonparametric estimation error is negligible under 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 a 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 implement 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:

$$\varepsilon_i^* = -c_0 - \left(c_1 - (\gamma)^{-\alpha}\right) x_i + \sum_{j \neq i} \frac{x_j\,(\gamma)^{-\alpha}}{N-1} \left[1 - \Phi\left(\frac{\varepsilon_j^* - \rho\varepsilon_i^*}{\sqrt{1-\rho^2}}\right)\right], \forall i = 1, 2, 3, \tag{28}$$

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 $P^{a_1 a_2 a_3}$, has in total eight elements:

$$P^{111} = \mathbb{P}\left(\varepsilon_1 \geq \varepsilon_1^*(X), \varepsilon_2 \geq \varepsilon_2^*(X), \varepsilon_3 \geq \varepsilon_3^*(X)\right), \tag{29}$$

$$P^{110} = \mathbb{P}\left(\varepsilon_1 \geq \varepsilon_1^*(X), \varepsilon_2 \geq \varepsilon_2^*(X), \varepsilon_3 < \varepsilon_3^*(X)\right), \tag{30}$$

$$P^{100} = \mathbb{P}\left(\varepsilon_1 \geq \varepsilon_1^*(X), \varepsilon_2 < \varepsilon_2^*(X), \varepsilon_3 < \varepsilon_3^*(X)\right), \tag{31}$$

$$P^{101} = \mathbb{P}\left(\varepsilon_1 \geq \varepsilon_1^*(X), \varepsilon_2 < \varepsilon_2^*(X), \varepsilon_3 \geq \varepsilon_3^*(X)\right), \tag{32}$$

$$P^{011} = \mathbb{P}\left(\varepsilon_1 < \varepsilon_1^*(X), \varepsilon_2 \geq \varepsilon_2^*(X), \varepsilon_3 \geq \varepsilon_3^*(X)\right), \tag{33}$$

$$P^{010} = \mathbb{P}\left(\varepsilon_1 < \varepsilon_1^*(X), \varepsilon_2 \geq \varepsilon_2^*(X), \varepsilon_3 < \varepsilon_3^*(X)\right), \tag{34}$$

$$P^{000} = \mathbb{P}\left(\varepsilon_1 < \varepsilon_1^*(X), \varepsilon_2 < \varepsilon_2^*(X), \varepsilon_3 < \varepsilon_3^*(X)\right), \tag{35}$$

$$P^{001} = \mathbb{P}\left(\varepsilon_1 < \varepsilon_1^*(X), \varepsilon_2 < \varepsilon_2^*(X), \varepsilon_3 \geq \varepsilon_3^*(X)\right). \tag{36}$$

The probabilities given in (29)-(36) 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

$$\mathcal{L}(\theta; X) = \sum_{g=1}^{G} \ln P^{a_{1g} a_{2g} a_{3g}}(\theta; X_g), \tag{37}$$

where $P^{a_{1g}a_{2g}a_{3g}}(\theta; X_g)$ denotes the probabilities defined in (29)-(36) 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 Comparing 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 simpler. However, the two-step estimator generates less efficient estimates with wider confidence intervals. On the other hand, the Nested Fixed Point method imposes 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. On page 49 in the Appendix, I provide the results from a Monte Carlo experiment to illustrate the finite sample performance of the these two above-mentioned estimation methods.

6.3 Estimation Results

In this section, I present the estimation results from applying the two-step MMSE and Nested Fixed Pointed methods to estimating the structural model discussed in Section 5 using the dataset introduced in Section 3. The sample includes 30 events ($G = 30$) and the state variable X is measured by the market share of platforms one week prior to each event using its respective traffic ranking data. Table 4 reports the parameter estimates from both estimation methods. These estimates are accompanied by bootstrapped 95% confidence intervals. The number of bootstrap replications is 500.

Table 4: 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]	[$\cdot$]	N/A
Nested Fixed Point Estimation	-0.5060**	1.7139**	1	0.3223**
	[-1.0632, -0.1784]	[1.2388, 2.6376]	[$\cdot$]	[0.0513 0.6749]

Notes to Table 4. Table 4 reports the parameter estimates of interests from both the two-step Modified Maximum Score Estimation and Nested Fixed Point Estimation. Recall that the two-step method does not specify the correlation structure of private signals and it requires a scale normalization. Thus, to generate comparable results between the two methods, I normalize $(\gamma)^{-\alpha}$ to 1. The bootstrapped 95% confidence intervals are in brackets. The number of bootstrap replications is 500.

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, for the small platform, the political cost net of economic gains ($c_1 - \gamma^{-\alpha}$) is dominated by its strategic incentives $\left(\frac{x_j}{(N-1)\gamma^{\alpha}}\right), j \in \{Big, Medium\}$. The last result suggests that, if this market becomes more concentrated, users are not necessarily more likely to experience censorship. I will further investigate the implications of this result through two counterfactual experiments in Section 7.

Model Fit Table 5 presents the observed and predicted censorship probability of each platform across the 30 unexpected events during 2015-2017. The model fits the observed level well, suggesting that the model is able to recover the market covariates that influence the censorship decisions of platforms in the arrival of an average event in my data.

Table 5: 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

Notes to Table 5. The first and second row of the table report respectively each platform's observed censorship frequency across the 30 unexpected events (described in Section 3) and the model-predicted censorship probability.

7 Counterfactual Predictions

Authoritarian governments are known for shutting down a firm at will if the firm does not comply with regulations. Why does the government allow those non-compliers to stay in business, instead of permanently shutting them down? Moreover, one might expect digital platforms to benefit from mergers and acquisitions due to strong network effects, especially given that live-streaming platforms in China provide "highly homogeneous products and content" to consumers (Liu and Li, 2016). Yet we observe a "very fragmented and localized" social media landscape in China (Chiu et al., 2012). From a regulator's perspective, do platform mergers always lead to higher level of compliance?

In this section, I simulate two counterfactual exercises that shed some light on these questions. First, I explore the scenario following a permanent shutdown of the smallest platform. Then I examine the case following a merger of the medium and small platforms[23] in the market. Finally I compare the results from the above two cases with those in an alternative setup where there is no strategic interaction between platforms under additional assumptions. Specifically, I define ΔSC as the percentage change in the the scope of censorship after such interventions, given by

$$\Delta SC \equiv [SC_{\text{after intervention}} - SC_{\text{before intervention}}]/SC_{\text{before intervention}}. \tag{38}$$

I assume that the correlation structure of private signals remains the same before and after the intervention.

Table 6 reports the simulation results. The point estimates are accompanied by bootstrapped 95% confidence intervals (in the square bracket). The number of bootstrap replications is 500. Both counterfactual exercises show that the existence of strategic incentives significantly moderates the increasing political pressure faced by platforms that usually follows market concentration. First, note that permanently shutting down the smallest platform

[23] As mentioned in Section 3, while the medium and small platforms are listed under the same parent company Tian Ge, they are now operated by two different subsidiary companies and manage their own keyword blacklists separately. Prior to this "merger" exercise, each platform owner makes censorship decisions only based on the expected traffic of their own platform and users can freely switch between the two platforms. However, after the "merger" exercise, two platforms become one with the new platform owner making censorship decisions based on the joint market share. Meanwhile, users can only switch out to the big platform but they can no longer "switch between" the medium and small platforms.

could backfire and lead to an unintended outcome where the overall level of compliance is lower in the marketplace. This is because if the smallest platform was no longer present, the remaining two platforms would share the whole market, both of which would have stronger strategic incentives to differentiate by not censoring. Their strategic incentives would increase as they would expect to attract more switching users from its then only competitor. In the absence of a non-compliant small platform, the surviving platforms comply significantly less often in equilibrium. As a result, market concentration turns out to push down the scope of censorship.

Table 6: Counterfactual Simulation Results

	Nested Fixed Point Estimation	
	Permanent Shutdown	Merging Two Platforms
ΔSC	-0.89%	-0.91%
	[-1.55%, -0.36%]	[-1.62%, -0.43%]
$\Delta \tilde{SC}$	4.41%	1.20%
(without strategic incentive)	[3.67%, 7.05%]	[0.60%, 1.85%]

Notes to Table 6. The first row in Table 6 reports the estimated percentage change in the scope of censorship in the market if the small platform is permanently shutdown (column 1) or if there is a merger between the medium and small platforms (column 2). The second row in Table 6 reports the counterpart results in the above two cases if the strategic incentives are terminated under the assumption that users cannot switch between platforms. The bootstrapped 95% confidence intervals are in brackets. The number of bootstrap replications is 500.

On the other hand, market concentration via merging two platforms also leads to a decline in the scope of censorship. While the merged two platforms censor more often than when they were separated due to higher political pressure, the big platform now competes with a much larger market player and thus has stronger strategic incentives to differentiate by not censoring. In this case, the latter effect dominates the former and thus the overall level of compliance in the market is lower following the merger. Note that, however, if we neglect the strategic incentives in platforms' decision-making process by assuming that users cannot switch between platforms[24], then market concentration would have led to an increase in the scope of censorship.

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

Finally, suppose the merger between two platforms is spontaneous and already complete, what then could the regulator do in order to maintain the pre-merger level of compliance? Based on some back-of-the-envelope calculations, the regulator could increase the regulatory pressure by imposing a higher cost of non-compliance on the big platform. This extra cost would translate to a loss of 0.71% of the platform's expected profit which is around 9 million US dollars in 2016. Alternatively, the regulator could mitigate platforms' strategic incentives by increasing users' switching cost, via, for instance, enforcing real-name registrations on social media platforms, so that the share of switching users ($\gamma^{-\alpha}$) decline by 50.12% on all platforms.

8 Conclusion

This paper studies the relationship between size distributions of online platforms and their compliance with censorship regulations under political pressure. 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. I show that while there were no pre-event traffic trends, post-event traffic significantly declined on all platforms.

Motivated by the empirical patterns, I propose a structural 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 countervailing 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 analyses suggest that merging or permanently shutting down small platforms both turn out to lower the equilibrium scope of censorship in the marketplace.

My findings suggest that decentralizing online market power could help an authoritarian government maintain sufficiently high market-level censorship with minimal enforcement. As opposed to directly imposing higher political penalties on all platforms, leveraging firms' differentiation incentives may seem an indirect and subtle strategy to achieve desired information control. However, it could turn out to be an effective alternative when the marginal cost of enforcement is already high. After all, there is a limit up to which the government can increase its political penalty without excessively disrupting the economy or inciting more protests. In fact, unlike the US market which is dominated by a handful of mainstream social media platforms, Chinese social media remains "very fragmented and localized (Chiu et al., 2012)."

Beyond China, the framework proposed in this paper also offers 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" (Bénabou and Tirole, 2016) 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, the number of keywords on a platform's blacklist may not be a perfect indicator for its censorship intensity because I do not directly observe the amount of messages censored by a platform. 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 the 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. Future research can extend the model and explore these issues.

References

Adamic, L. A. (2000). Zipf, power-laws, and pareto-a ranking tutorial. *Xerox Palo Alto Research Center, Palo Alto, CA, http://ginger. hpl. hp. com/shl/papers/ranking/ranking. html.*

Anderson, E. T., Fong, N. M., Simester, D. I., and Tucker, C. E. (2010). How sales taxes affect customer and firm behavior: The role of search on the internet. *Journal of Marketing Research*, 47(2):229–239.

Aradillas-Lopez, A. and Gandhi, A. (2013). Robust inference of strategic interactions in static games. Technical report, University of Wisconsin working paper.

Arnold, A. (2018). Do we really need to start regulating social media?

Athey, S. (2001). Single crossing properties and the existence of pure strategy equilibria in games of incomplete information. *Econometrica*, 69(4):861–889.

Bajari, P., Hong, H., Krainer, J., and Nekipelov, D. (2006). Estimating static models of strategic interaction. Technical report, National Bureau of Economic Research.

Bamman, D., O'Connor, B., and Smith, N. (2012). Censorship and deletion practices in chinese social media. *First Monday*, 17(3).

Bénabou, R. and Tirole, J. (2016). Mindful economics: The production, consumption, and value of beliefs. *Journal of Economic Perspectives*, 30(3):141–64.

Bramoullé, Y., Djebbari, H., and Fortin, B. (2009). Identification of peer effects through social networks. 150(1):41–55.

Brewster, J. (2020). As twitter labels trump tweets, some republicans flock to new social media site. *The Forbes*.

Chao, G. H., Iravani, S. M., and Savaskan, R. C. (2009). Quality improvement incentives and product recall cost sharing contracts. *Management Science*, 55(7):1122–1138.

Chen, Y. and Yang, D. Y. (2019). The impact of media censorship: 1984 or brave new world? *American Economic Review*, 109(6):2294–2332.

Chiu, C., Ip, C., and Silverman, A. (2012). Understanding social media in china. *McKinsey Quarterly*.

Crandall, J. R., Crete-Nishihata, M., Knockel, J., McKune, S., Senft, A., Tseng, D., and Wiseman, G. (2013). Chat program censorship and surveillance in china: Tracking tom-skype and sina uc. *First Monday*, 18(7).

De Paula, A. and Tang, X. (2012). Inference of signs of interaction effects in simultaneous games with incomplete information. *Econometrica*, 80(1):143–172.

Dukes, A. (2004). The adverstising market in a product oligopoly. *The Journal of Industrial Economics*, 52(3):327–348.

Dukes, A. J. (2006). Media concentration and consumer product prices. *Economic Inquiry*, 44(1):128–141.

Durante, R. and Knight, B. (2012). Partisan control, media bias, and viewer responses: Evidence from berlusconi's italy. *Journal of the European Economic Association*, 10(3):451–481.

Edmond, C. (2013). Information manipulation, coordination, and regime change. *The Review of Economic Studies*.

Gal-Or, E. and Dukes, A. (2003). Minimum differentiation in commercial media markets. *Journal of Economics and Management Strategy*, 12(3):291–325.

Gehlbach, S. and Sonin, K. (2014). Government control of the media. *Journal of Public Economy*, 118:163–171.

Gentzkow, M. and Shapiro, J. M. (2010). What drives media slant? evidence from us daily newspapers. *Econometrica*, 78(1):35–71.

Gentzkow, M., Shapiro, J. M., and Sinkinson, M. (2014). Competition and ideological diversity: Historical evidence from us newspapers. *The American Economic Review*, 104(10):3073–3114.

Geron, T. (2012). Yy.com: China's unique real-time voice and video service with a virtual goods twist.

Groseclose, T. and Milyo, J. (2005). A measure of media bias. *The Quarterly Journal of Economics*, 120(4):1191–1237.

Harsanyi, J. C. (1973). Games with randomly disturbed payoffs: A new rationale for mixed-strategy equilibrium points. *International Journal of Game Theory*, 2(1):1–23.

Hobbs, W. R. and Roberts, M. (2018). How sudden censorship can increase access to information. *American Political Science Review*.

Human Rights Watch (2006). Corporate complicity in chinese internet censorship. 18(8(C)).

Initiative, O. (2005). Internet filtering in china 2004–2005: A country study. *URL (consulted March 2007): http://www. opennetinitiative. net/studies/china.*

King, G., Pan, J., and Roberts, M. (2013). How censorship in china allows government criticism but silences collective expression. *Am Polit Sci Rev*, 107(02):326–343.

Knockel, J. (2016). One app, two systems: How wechat uses one censorship policy in china and another internationally. *Citizen Lab, Munk School, University of Toronto*.

Knockel, J., Crete-Nishihata, M., Ng, J. Q., Senft, A., and Crandall, J. R. (2015). Every rose has its thorn: Censorship and surveillance on social video platforms in china. In *5th USENIX Workshop on Free and Open Communications on the Internet (FOCI 15)*. USENIX Association.

Liu, R. and Li, D. (2016). The pulse of live streaming in china: Understanding the new chinese lifestyle and the business behind it. *China Tech Insights*.

Lomas, N. (2017). Facebook, twitter still failing on hate speech in germany as new law proposed. *Tech Crunch*.

Lorentzen, P. (2014). China's strategic censorship. *American Journal of Political Science*.

Manski, C. F. and Tamer, E. (2002). Inference on regressions with interval data on a regressor or outcome. *Econometrica*, 70(2):519–546.

Miller, B. (2017). The limits of commercialized censorship in china.

Mullainathan, S. and Shleifer, A. (2002). Media bias. Technical report, National Bureau of Economic Research.

Newberry, C. (2019). 130+ social media statistics that matter to marketers in 2019.

Newton, C. (2019). Why social networks keep tripping over their own content moderation policies. *The Verge*.

Nooren, P., van Gorp, N., van Eijk, N., and Fathaigh, R. Ó. (2018). Should we regulate digital platforms? a new framework for evaluating policy options. *Policy and Internet*, 10(3):264–301.

Oltermann, P. (2018). Tough new german law puts tech firms and free speech in spotlight. *The Guardian*.

Orhun, A. Y., Venkataraman, S., and Chintagunta, P. K. (2015). Impact of competition on product decisions: Movie choices of exhibitors. *Marketing Science*, 35(1):73–92.

Prat, A. and Strömberg, D. (2013). The political economy of mass media. advances in economics and econometrics: Theory and applications. In *Proceedings of the Tenth World Congress of the Econometric Society. Cambridge University Press, Cambridge*.

Qin, B., Strömberg, D., and Wu, Y. (2016). The political economy of social media in china. Technical report.

Qin, B., Wu, Y., and Strömberg, D. (2018). The determinants of media bias in china. volume 108, pages 2442–2476.

Stern, R. E. and Hassid, J. (2012). Amplifying silence: uncertainty and control parables in contemporary china. *Comparative Political Studies*, 45(10):1230–1254.

Sweeting, A. (2004). Coordination games, multiple equilibria and the timing of radio commercials. *Journal of Economics and Management Strategy*.

Sweeting, A. (2009). The strategic timing incentives of commercial radio stations: An empirical analysis using multiple equilibria. *The RAND Journal of Economics*, 40(4):710–742.

Wan, Y. and Xu, H. (2014). Semiparametric identification of binary decision games of incomplete information with correlated private signals. *Journal of Econometrics*, 182(2):235–246.

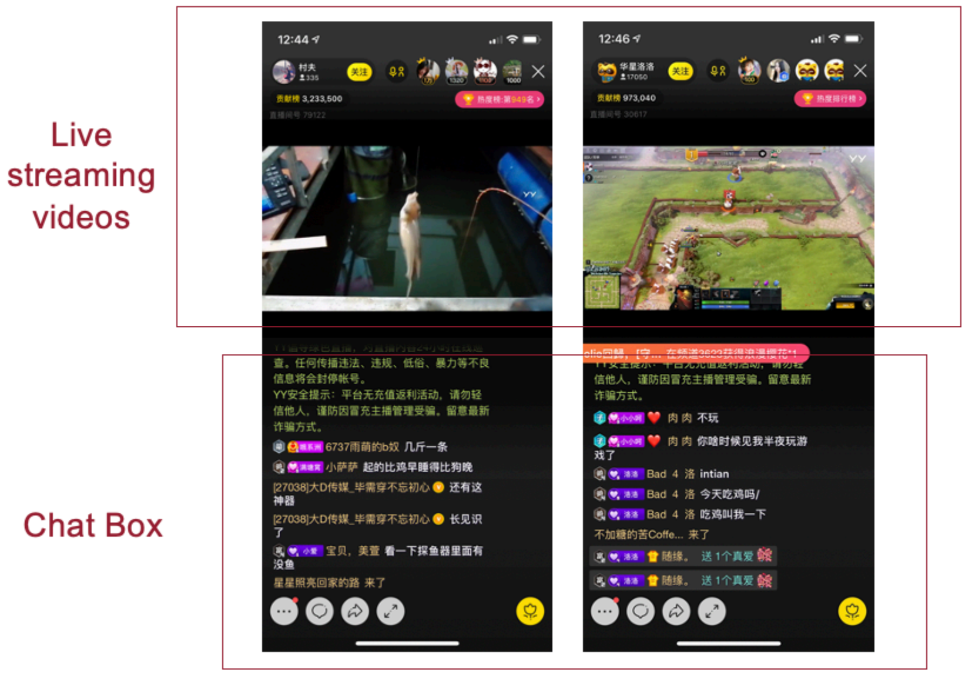
Yildirim, P., Gal-Or, E., and Geylani, T. (2013). User-generated content and bias in news media. *Management Science*, 59(12):2655–2666.

Zhang, K. and Sarvary, M. (2011). Social media competition: Differentiation with user generated content. *Marketing Science*, 47:48.

Appendices

Appendix A: Exhibits

Figure 6: A screenshot of YY's user interface



Notes to Figure 6. This is an example screenshot of the mobile user interface on one of the platforms (YY) in my study. The live-streaming videos appear on the top of the screen and a chat box is located at the bottom of the screen. Users could interact with each other by typing their messages in the chat box. Their messages are public to all users who are watching the video in the room.

Appendix B: 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. Let $\delta_j(x) \equiv \frac{x_j}{(N-1)(\gamma)^\alpha}$. First, note that for any $i \in \{1, 2, ..., N\}$ and $(t, x) \in \mathbb{R} \times \Omega_X$, we have

$$\sum_{j \neq i} \delta_j(x)[\frac{\partial \mathbb{P}(\varepsilon_j \geq t|X, \varepsilon_i)}{\partial \varepsilon_i}] = -\sum_{j \neq i} \frac{x_j}{(N-1)(\gamma)^\alpha}[\frac{\partial \mathbb{P}(\varepsilon_j \geq t|X, \varepsilon_i)}{\partial \varepsilon_i}] \tag{39}$$

$$>= -\sum_{j \neq i} x_j \tag{40}$$

$$> -1 \tag{41}$$

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

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

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

$$\varepsilon_i^*(x) = -\beta_0 - \beta_1 x_i - \sum_{j \neq i} \delta_j \mathbb{P}(\varepsilon_j \geq \varepsilon_j^*(x) | X = x, \varepsilon_i) \tag{42}$$

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

$$
\begin{aligned}
||\Gamma'(\varepsilon)||_\infty &= \max_{1\le i\le N} \sum_{j=1}^{N} |\Gamma'_{ij}| && (43)\\
&= \max_{1\le i\le N} \left(|\Gamma'_{ii}| + \sum_{j\neq i}^{N} |\Gamma'_{ij}| \right) && (44)\\
&= \max_{1\le i\le N} \sum_{j\neq i} |\delta_j| \left(\frac{\partial \mathbb{P}(\varepsilon_j \ge \varepsilon_j(x)|X=x,\varepsilon_i)}{\partial \varepsilon_i} + \left| \frac{\partial \mathbb{P}(\varepsilon_j \ge \varepsilon_j(x)|X=x,\varepsilon_i)}{\partial \varepsilon_j} \right| \right) && (45)\\
&\le \sum_{j\neq i}^{N} x_j && (46)\\
&< 1, && (47)
\end{aligned}
$$

where the second last inequality follows Assumption 1. □

Proof of Theorem 2:

Suppose that $\mathbb{P}(\varepsilon_{-i} \ge t|X = x, \varepsilon_i)$ 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

$$\varepsilon_i^*(x) = -\beta_0 - \beta_1 x_i - \sum_{j\neq i} \delta_j \mathbb{P}(\varepsilon_j \ge \varepsilon_j^*(x)|X = x, \varepsilon_i) \tag{48}$$

Since the equilibrium is an MPSE, it follows that

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

Let $\sigma_{ij}(x) \equiv \mathbb{P}(\varepsilon_j \ge \varepsilon_j^*(x)|X = x, \varepsilon_i = \varepsilon_i^*(x))$. 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

$$\mathbb{1}[\varepsilon_i \geq -\beta_0 - \beta_1 x_i - \sum_{j\neq i} \delta_j(x)\sigma_{ij}^1(x)] \leq a_i \leq \mathbb{1}[\varepsilon_i \geq -\beta_0 - \beta_1 x_i - \sum_{j\neq i} \delta_j(x)\sigma_{ij}^0(x)] \tag{49}$$

□

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 $t \to 1$. $\square$

Appendix C: 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 experiment 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 is easy to show that Assumption 1 - 3 are satisfied under these parametrizations. Thus a unique Monotone Pure Strategy Equilibrium exists.

For each x, I compute cutoff values $\varepsilon_i^*(x)$ using equation (15). Table 7 reports the mean and standard deviation (in parentheses) of the two-step Modified Maximum Score and Nested Fixed Point estimators under different specifications and sample sizes. All results are based on $S = 500$ replications.

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.

Table 7: 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)

Notes to Table 7. Table 7 reports the mean and standard deviation (in parentheses) of the two-step Modified Maximum Score and Nested Fixed Point estimators under different specifications and sample sizes. All results are based on $S = 500$ replications.

Appendix D: Event Classification and References

Table 8: 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	Hooligan Sparrow	22-Jan-16	X	
12	Ezubao	1-Feb-16	X	
13	Oscars 2016	28-Feb-16	X	
14	HongKong Localist LegCo Plans	29-Feb-16	X	
15	Trump's Comment on Tiananmen Proteset	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	Hong Kong Booksellers	16-Jun-16	X	
21	Wukan Mass 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	
26	Xi and Trump Meeting	7-Apr-17	X	
27	Blue Whale Suicide Incidence	9-May-17	X	
28	Uyghurs celebrating the Ramadan Holiday	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 Protest	4-Jun-89		X
34	Falun Gong 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 9: 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 accidentally live-streamed herself having sex on the platform and triggered broad online discussions about tightening regulations on censoring live-streaming platforms.

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 incident 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 Chinese government and came to Munich for medical examinations in August 2015.

7 ISIL Beheading Incidents Khaled al-Asaad, aged 81, was beheaded in Tadmur on August 18, 2015. Al-Asaad was accused by ISIL of being an "apostate." Information about ISIL is strictly controlled by the Chinese authorities due to the growing tension between Muslim Uyghur minority and the government.

8 Hong Kong 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 November 13, 2015 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 at the Sundance Film Festival in January 2016. The movie featured her being chased by local governments and national secret police from town to town in China.

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 Oscars 2016 Popular online streaming sites in China abruptly canceled plans to live broadcast the 88th Academy Awards on the eve of the Oscars night. 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's 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 TianGuo Marching Band Over 20,000 residents in San Francisco signed a petition showing 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 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 went on 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 calling 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." Chinese netizens made fun of Xi and made up several euphemisms about this incidence.

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 April 7, 2017. 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 were stabbed to death in Jiangyin, Wuxi, a town in east China. The Chinese government considered this a very serious social event that disrupted public order and might cause distrust of the police force as well as the government.

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-favored candidate. She beat 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 Protest 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 February 20, 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 September 22, 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.

Table 10: News Sources of Events

1 https://freetibet.org/news-media/na/mother-two-carries-out-self-immolation-protest

2 http://www.independent.co.uk/news/world/asia/chinese-artist-who-posted-funny-image-of-president-xi-jinping-facing-five-years-in-prison-as-10282630.html

3 http://www.wsj.com/articles/chinas-former-security-chief-zhou-yongkang-sentenced-to-life-in-prison-1434018450

4 http://www.ibtimes.com.cn/articles/45646/20150808/36076.htm

5 https://en.wikipedia.org/wiki/2015_Tianjin_explosions

6 https://en.wikipedia.org/wiki/ISIL_beheading_incidents

7 https://www.theguardian.com/world/2016/sep/05/hong-kong-poll-pro-independence-activists-poised-to-win-seats-in-record-turnout

8 http://www.bbc.com/news/world-europe-34818994

9 https://www.ft.com/content/4c3e703e-9fd6-11e5-beba-5e33e2b79e46

10 https://theinitium.com/article/20160122-opinion-hooligansparrow

11 http://www.imdb.com/title/tt4079902

12 https://en.wikipedia.org/wiki/Ezubao

13 http://chinadigitaltimes.net/2016/02/china-cheers-dicaprios-oscar-win-though-online-broadcasts-halted

14 https://www.hongkongfp.com/2016/02/29/localist-groups-announce-action-plan-for-sept-legco-election-as-cy-urged-to-reflect-on-by-election-result

15 https://www.washingtonpost.com/news/worldviews/wp/2016/03/11/trump-just-called-tiananmen-square-a-riot-the-communist-party-will-be-pleased/?utm_term=.53d595ad1979

16 http://www.theepochtimes.com/n3/1334123-new-york-parade-continues-changes-begun-16-years-ago-in-china

17 https://www.theguardian.com/world/2016/may/04/china-release-last-prisoner-tiananmen-square-protests

18 http://www.rfa.org/mandarin/yataibaodao/renquanfazhi/ql2-05042016102740.html

19 http://thediplomat.com/2016/08/chinas-nightmare-xinjiang-jihadists-go-global/

20 https://en.wikipedia.org/wiki/Causeway_Bay_Books_disappearances

21 http://chinadigitaltimes.net/2016/06/wukan-villagers-protest-village-chiefs-detention

22 https://en.wikipedia.org/wiki/Philippines_v._China

23 https://www.hongkongfp.com/2016/09/06/president-xi-jinpings-take-off-clothes-g20-gaffe-censored-in-china

24 https://www.reuters.com/article/us-china-military/chinese-military-veterans-stage-protests-in-central-beijing-over-pensions-idUSKBN1620G5

25 http://www.epochtimes.com/gb/17/3/13/n8903779.html

26 http://www.bbc.com/zhongwen/simp/world-39524474

27 https://web.archive.org/web/20170511020715/http://news.163.com/17/0510/14/CK34UFUH000187VE.html

28 https://www.express.co.uk/news/world/809957/Ramadan-2017-date-start-end-Muslim-fast-explained-when-why-eid

29 http://toutiao.china.com/app/social/13000654/20170629/30868213.html

30 https://en.wikipedia.org/wiki/Carrie_Lam

31 https://www.theguardian.com/world/2009/sep/30/china-national-day-parade-communism

32 http://www.bbc.com/news/world-asia-china-36299692

33 https://en.wikipedia.org/wiki/Tiananmen_Square_protests_of_1989

34 https://en.wikipedia.org/wiki/Persecution_of_Falun_Gong

35 https://en.wikipedia.org/wiki/2008_Sichuan_earthquake

36 https://en.wikipedia.org/wiki/Charter_08

37 http://en.wikipedia.org/wiki/16th_National_Congress_of_the_Communist_Party_of_China

38 https://en.wikipedia.org/wiki/July_2009_Urumqi_riots

39 http://www.thatsmags.com/guangzhou/post/6005/guangzhou-activists-campaign-to-make-today-cantonese-day

40 https://en.wikipedia.org/wiki/Arab_Spring

41 https://en.wikipedia.org/wiki/2011_Chinese_pro-democracy_protests

42 https://en.wikipedia.org/wiki/Wenzhou_train_collision

43 http://www.theguardian.com/world/2012/feb/28/china-riots-dead

44 https://zh.wikipedia.org/wiki/%E4%BA%AC%E6%B8%A9%E4%BA%8B%E4%BB%B6

45 https://en.wikipedia.org/wiki/Bo_Xilai

46 http://www.guardian.co.uk/world/2012/sep/03/china-scandal-fatal-ferrari-crash

47 http://www.ibtimes.co.uk/china-hua-zang-dharma-cult-leader-wu-zeheng-faces-rape-fraud-charges-1511143

48 https://en.wikipedia.org/wiki/18th_National_Congress_of_the_Communist_Party_of_China

49 https://en.wikipedia.org/wiki/Umbrella_Movement