The Effect of Over-the-Top Media Services on Piracy Search: Evidence from a Natural Experiment

Shijie Lu
Assistant Professor of Marketing
Bauer College of Business
University of Houston
slu@bauer.uh.edu

Koushyar Rajavi
Assistant Professor of Marketing
Scheller College of Business
Georgia Institute of Technology
krajavi3@gatech.edu

Isaac Dinner
Director of Econometric Modeling
Indeed
isaac@isaacdinner.com

Abstract

The rise of over-the-top (OTT) video streaming services has raised the question of how this new form of digital media affects consumer search for pirated content. We address this question by using Netflix's unexpected announcement of a global market expansion in January 2016 and the subsequent block by the primary telecommunications firm in Indonesia as an exogenous shock to the supply of OTT services in that country. Using synthetic control methods, we compare the change in piracy search between Indonesia and 40 Asian countries where Netflix simultaneously entered and remained available. Netflix's failure to launch in Indonesia leads to a 19.7% increase in search for pirated movies and TV shows in Indonesia, relative to the other countries, suggesting a net substitution of piracy for OTT services. Comparison of treatment effects between exclusive and nonexclusive content shows that the treatment effect is driven by both a combination of an expansion of the market for piracy and a substitution between piracy and OTT services. We also find that the treatment effect is stronger for less dialogue-oriented content, which is consistent with the greater appeal of dialogue-light content to non-English-speaking consumers.

Keywords: piracy, over-the-top service, video streaming, synthetic control, natural experiment

1. Introduction

In 2018, the Video Advertising Bureau estimated that 71% of U.S. households accessed media through an over-the-top (OTT) media service and that the number of U.S. households that solely use OTT services rapidly increased from 5 million in 2013 to more than 14 million in 2017. The growing popularity of OTT services in the United States also coincides with an increasingly large number of OTT service providers globally. While U.S. consumers are likely most familiar with Netflix, Hulu, and Amazon Prime, there exist a substantial number of international options at widely affordable price points: Spuul is popular in India, Showmax in South Africa, and Viaplay in Finland. There are also growing niche players focused on specific genres such as horror (Shudder) or cinematic classics (Mubi). The popular press speculates that the introduction of these high value, low cost, media services can help bring down global piracy (ZDNet 2016). However, these arguments are largely correlational and have not been supported by rigorous empirical evidence.

Theoretically, OTT media services may affect piracy in two opposing ways. First, the introduction of a reasonably priced on-demand substitute may be so attractive that many consumers will discontinue consuming pirated content in favor of the OTT service. It is therefore possible that the introduction of OTT services will induce the piracy market to shrink, suggesting a substitution effect. Prior research suggests that consumers may turn from piracy to legal channels for any number of reasons. For example, unlike piracy channels, which often require consumers to proactively search for desired content, legal digital distribution channels significantly lower the search cost (Hennig-Thurau et al. 2007). Other possible reasons include the guaranteed high-quality video content available on OTT platforms and the lack of legal, moral, or technical risks typically associated with pirated content (Hennig-Thurau et al. 2007, Danaher et al. 2010, Smith and Telang 2016). Second, the market for pirated content may increase as a result of OTT services. In particular, word of mouth (WOM) and promotional activities may spread product information associated with OTT services, leading consumers to search for alternative outlets. For example, an article about female inmates in the *New York Times,* during the promotion of the show *Orange Is the New Black* (Deziel 2014), may have triggered consumers' awareness of and interest in the show and consequently driven some consumers to watch the show from piracy sites instead of Netflix. This suggests a market expansion effect of OTT services on piracy. Because both substitution and market expansion effects may occur, whether the introduction of an OTT service will lead to a decrease or an increase in the demand for piracy is not clear.

The main goal of this research is to quantify the effect of OTT services on consumer search for piracy by examining a unique natural experiment. On January 6, 2016, Netflix announced that it would immediately become available in 130 new countries (41 in Asia), including Indonesia (Minaya and Sharma 2016). However, on January 27, 2016, the dominant telecommunications provider in Indonesia blocked the Netflix service due to governmental concerns (Yuniar 2016). In this natural experiment we define the treatment to be Netflix's failure to launch in Indonesia, which provided a natural shock to the availability of OTT services in Indonesia. Accordingly, Indonesia is the only country in which Netflix entered but was subsequently blocked and thus is the only treated unit. The remaining 40 countries in Asia, where Netflix entered at the same time and remained available, constitute a control group.

To investigate the effect of the treatment on piracy demand, we collected monthly piracy search data from Google for a sample of 304 Netflix titles, including both movies and TV shows, in 41 Asian countries (including Indonesia) between October 2014 and June 2016. We begin by considering a difference-in-differences (DiD) model, which compares the relative change in search for pirated content (hereafter called piracy search) between Indonesia and the 40 control countries before and after treatment. The results show a significantly positive short-term effect of the treatment on piracy search in Indonesia relative to the 40 control countries. Nevertheless, the path of piracy search in control countries does not match well with Indonesia during the pretreatment period from October 2014 to December 2015. As such, in the main analysis, we use a synthetic control method (Abadie et al. 2010, 2015), which Athey and Imbens (2017, p. 9) call "arguably the most important innovation in the evaluation literature in the last 15 years." The synthetic control method extends the DiD framework by allowing the effect of unobserved confounders on the outcome to vary over time (Abadie et al. 2010). With this approach, we construct a synthetic control country by allowing different potential control countries to have different weights. We then compare the change in search volume in Indonesia with that in the synthetic control country to estimate the treatment effect.

We find that Netflix's failure to launch in Indonesia leads to a 19.7% increase in search for pirated movies and TV shows in Indonesia relative to the other 40 countries where Netflix entered and remained available, suggesting a net substitution effect of OTT services on piracy. Additional support comes from the observation that the difference between Indonesia and these other countries disappears when alternative OTT services became available in Indonesia. However, despite the net displacement between OTT services and piracy, do OTT services also expand the piracy market?

We provide evidence of the market expansion effect by investigating the differential effect of the treatment between original content exclusively distributed by Netflix and nonoriginal content licensed by Netflix, which is also available on other legal distribution channels. If the positive effect of Netflix's unavailability in Indonesia on piracy search is driven solely by substitution, we expect this effect to be stronger for original content than for nonoriginal content. This is because nonoriginal content is available on multiple legal distribution channels, while original content is exclusive to Netflix, implying a higher level of substitution between Netflix and piracy for original content. Conversely, if the introduction of OTT services also expands the piracy market, we expect the associated negative effect of Netflix's unavailability in Indonesia on piracy search to be stronger for original content than for nonoriginal content because of increased WOM and a higher promotional effort for original content. In essence, the existence of a substitution effect alone would indicate that Netflix's failure to launch in Indonesia results in a more positive effect on piracy search for original than nonoriginal content. Our finding of a less positive treatment effect for original than nonoriginal content is consistent with the coexistence of both a substitution and a market expansion effect rather than just a substitution effect.

We also explore the moderating role of dialogue orientation in the effect of Netflix's unavailability in Indonesia on piracy search. Given that the majority of Netflix titles (96.7%) are not in the local languages of the 41 Asian countries, less dialogue-oriented titles tend to be more appealing to Asian consumers because of lower language barriers. As a result, we expect a stronger substitution effect of the availability of OTT service on piracy search for less dialogue-oriented titles. For each title, we measure the degree of dialogue orientation using the average number of words per minute. We find a greater treatment effect for less dialogue-oriented titles using multiple methods of classifying dialogue orientation, which offers evidence of the hypothesized moderating effect of dialogue orientation.

We contribute to the piracy literature by providing new evidence for the substitution of media consumption between legitimate and illegitimate channels. Specifically, we show a positive effect of the unavailability of an OTT service on the search for pirated content. Compared with previous studies, we identify the effect based on an exogenous supply shock at the service, rather than content level, which makes the control less likely to be affected by the shock and therefore provides a cleaner setting for identification. We quantify the treatment effect using a synthetic control method, which extends the commonly used DiD method by selecting the control in a more data-driven manner. We also examine the moderating effects of content exclusivity and dialogue orientation, both of which are novel.

2. Related Literature

This article draws from the literature on digital piracy in marketing, economics, and information systems. Early research on digital piracy primarily focused on the software and music industries, and generally found displacement between legal and illegal sales (Givon et al. 1995, Rob and Waldfogel 2006, Zentner 2006).[1] More recent empirical studies on video piracy reveal mixed evidence on how piracy affects sales. Rob and Waldfogel (2007) examine the effect of piracy on DVD purchases and find that video piracy has a relatively higher rate of substitution but a more modest overall effect on sales than music piracy. Using a longitudinal survey data of German consumers, Hennig-Thurau et al. (2007) also find that illegal consumer file sharing significantly hurts theater visits, DVD rentals, and DVD purchases. Ma et al. (2014) show that prerelease piracy negatively affects box office revenues. Danaher and Smith (2014) find that the shutdown of a major piracy site positively affects digital sales and rentals of movies from major

[1] A notable exception is Oberholzer-Gee and Strumpf (2007), who find little evidence of a link between digital music downloads and sales, though subsequent analysis of their data shows alternative results (Liebowitz 2016). For a review of early research on piracy, see Danaher et al. (2014).

studios, again suggesting a substitution of piracy for legal content consumption. By contrast, when examining the relationship between DVD sales and the availability of a pirated copy during a broadcast TV window after theatrical release, Smith and Telang (2009) find no evidence of the detrimental effects of piracy. Peukert et al. (2017) find a negative effect of the shutdown of a popular piracy site on box office revenues of an average movie and explain their findings by the WOM effect of online piracy. Lu et al. (2020) find a positive relationship between postrelease piracy and box office revenues and show that WOM drives this positive relationship. Following Peukert et al. (2017) and Lu et al. (2020), we theorize a potential market expansion effect of the introduction of a legal distribution channel on illegal content consumption through an increase in associated WOM and promotion.

Previous research suggests that piracy consumption incurs multiple types of nonfinancial costs, even though accessing content through piracy is generally considered "free" (Hennig-Thurau et al. 2007, Danaher et al. 2010, Smith and Telang 2016). The most obvious cost is legal. In particular, there are file sharing cases where individuals have been fined upwards of $675,000 (BBC 2012). There are also nonfinancial costs which include learning how to use specific software to download content from torrent sites. Technical costs may exist due to the possibility of downloading malware when using torrent software, and time spent finding the online content creates a search cost. Finally, there are moral costs about whether piracy is equivalent to theft. These costs provide the theoretical underpinnings for why the introduction of a legal distribution channel, such as an OTT service, may decrease the demand for piracy and thus have a substitution effect.

Most previous piracy research focuses on how piracy affects demand for legal content and relatively less attention has been devoted to examining how legal distribution channels affect the demand for piracy. Three studies have made notable progress in this area. Danaher et al. (2010) use the removal of NBC shows from the Apple iTunes store to identify the effect of a digital distribution channel on sales from both physical channels and piracy channels. Their results show that the removal of NBC content led to an 11.4% increase in demand for NBC's pirated content but no change in demand for NBC's DVD content. Danaher et al. (2015) use the addition of ABC shows to Hulu in 2008 as a natural shock and find that piracy decreased by 20% for the four weeks after the addition of ABC shows. De Matos et al. (2018) examine the effect of OTT services on piracy consumption by randomly giving a sample of active cable and BitTorrent users temporary access to a TV "cinema" package. They find that the provision of this TV add-on increased TV viewing and decreased general Internet usage, but did not significantly decrease BitTorrent downloads.

Our research extends these three studies in several ways. First, we propose a new and relatively cleaner identification strategy to examine the effect of an OTT service on piracy using the service-level rather than content-level supply shock. A focus on the supply shock at the service level helps alleviate concerns about spillover effects. That is, the treatment may affect the behavior of consumers in the control group. For example, the removal of NBC content from iTunes (Danaher et al. 2010) may have affected consumers' viewing behavior of content produced by control channels. Second, we use a synthetic control method, which extends the DiD method by selecting the control in a more data-driven manner (Abadie et al. 2010, 2015). The synthetic control method is suitable for this empirical context because of the relatively large donor pool (40 control countries). Research has also used this method to assess the effect of TV advertising on online chatter (Tirunillai and Tellis 2017), the effect of opening a physical showroom on sales (Li 2019), and the engagement and spillover effects of newspaper paywalls (Pattabhiramaiah et al. 2019). Third, we explore the heterogeneity of the treatment effect by content exclusivity and dialogue orientation.

3. Natural Experiment

3.1. Netflix and Its Global Market Expansion

Netflix was founded in the United States in August 1997 with an initial business model focused on DVD rental by mail. In 2007, Netflix expanded its business by introducing streaming video on demand via the Internet (Hardy 2007). With the growth in consumer demand for streaming content, Netflix began shifting away from its initial core business of renting DVDs while investing heavily in the streaming platform. After the market showed traction for streaming content, Netflix began slowly expanding into international markets. In 2010, Canada became the first international market in which Netflix's streaming services became available (Nowak 2010). In 2011, Netflix became available in Mexico, Central America, and the Caribbean (Netflix 2011), followed by expansion to select European countries in 2012 (PR Newswire 2012). By the end of 2015, Netflix was available to 65 million members across 60 countries (Carter 2015). Despite the initial success of global market expansion, Netflix was still only available in less than one-third of all potential global markets.

On January 6, 2016, at the Consumer Electronics Show, Netflix announced that its service would be immediately available to 130 additional countries around the world (Netflix 2016).[2] This was a major market expansion of its services, as overnight it more than tripled the number of countries in which it operated. As a result, Netflix became available globally in all countries except China, Crimea, North Korea, and Syria (Stelter 2016).

3.2. Failure to Launch in Indonesia

Despite Netflix's intention to remain available in 130 new countries, it failed to do so in Indonesia. On January 27, 2016, Indonesia's state-owned telecommunications provider, Telekomunikasi Indonesia (or Telkom), blocked access to Netflix because Netflix did not have a permit to operate as a content provider in Indonesia (Yuniar 2016). Telkom also shared the Indonesian Film Censorship Board's concerns about violent and adult content on Netflix. While other telecommunications options are available in Indonesia, Telkom is clearly the dominant network. OTT services are most cost-effective for consumers on fixed lines, and Telkom has a near monopoly of wired networks, commanding 85.7% market share as of 2016 (Frost 2018). The second player, Indosat, and other smaller providers, had a primary corporate focus on voice and SMS instead of data, which make them a poor fit for OTT service usage. The block by Telkom had a clear impact on Netflix's availability in Indonesia and was not anticipated by Netflix. Using data from Google Trends, we show in Figure 1 that searches for the term "Netflix" spiked on January 6, 2016, and again at the end of January 2016, when Netflix was blocked in Indonesia. These spikes suggest that neither Netflix's intended introduction nor Telkom's block was anticipated by Indonesian consumers.

[2] For the full list of countries where Netflix became available in January 2016, see Stelter (2016).

After the block, searches for "Netflix" dropped considerably, nearly reverting to the preintroduction levels when Netflix was not available in Indonesia.

< Insert Figure 1 about here >

Netflix's failure to launch served as a natural shock to the availability of OTT services in Indonesia. We therefore define the treatment as Netflix's *failure to launch* in Indonesia.[3] Indonesia is the only treated country where Netflix entered but was subsequently blocked. The remaining countries constitute the control set in which Netflix both entered and remained available.

Netflix remained largely unavailable in Indonesia until April 2017, when it reached an agreement with Telkom (Cher 2017). Through this agreement, Telkom formed a strategic partnership with Netflix, which resulted in the unblocking of Netflix's content in Indonesia on April 12, 2017 (Maulani 2017). The period between Netflix's block in Indonesia on January 27, 2016, and unblock on April 12, 2017, creates an appropriate posttreatment period for a natural experiment. However, Telkom allowed several local competitors of Netflix to enter the Indonesian market between January 2016 and April 2017. The most important entry was by iflix, a Malaysian streaming platform targeting emerging markets in Asia and, to a lesser extent, Africa. Iflix entered Indonesia on June 16, 2016 (Piar Consulting 2016), suggesting that the supply of OTT services increased after June 16, 2016. To avoid any confounding effects due to the availability of other OTT services in Indonesia, we narrow the posttreatment window to the period between January 27, 2016, and June 16, 2016, during which OTT services were largely unavailable in Indonesia. We henceforth focus on a short-term rather than long-term treatment effect in this research.

4. Data

We collect data on multiple countries, titles, and measures. For countries, we compare piracy demand in Indonesia with a broader set of Asian countries where Netflix entered and remained available. For video

[3] In comparative case studies it is conventional to call the single country where certain events or interventions occurred as "treated" and the remaining countries as "controls" (Abadie et al. 2010). We follow previous synthetic control literature and define the treatment as "Netflix's failure to launch" rather than "Netflix's availability," given our focus on the event occurring solely in Indonesia.

content, we focus on Netflix titles that were widely available in these countries. For piracy demand, we collect data on piracy search at the title–country–month level using multiple phrases.

4.1. Control Countries

While all other 129 countries in which Netflix entered and remained available could serve as a control unit, to make the scope of data collection manageable, we focus on the 40 Asian countries in which Netflix was introduced in January 2016 and remained available. The list includes 10 countries in Southeast Asia (Brunei, Cambodia, Laos, Malaysia, Myanmar, the Philippines, Singapore, Thailand, Timor-Leste, and Vietnam), five countries in East Asia (Hong Kong, Macau, Mongolia, South Korea, and Taiwan), eight countries in South Asia (Afghanistan, Bangladesh, Bhutan, India, the Maldives, Nepal, Pakistan, and Sri Lanka), 12 countries in West Asia (Armenia, Azerbaijan, Bahrain, Iraq, Kuwait, Oman, Palestine, Qatar, Saudi Arabia, Turkey, United Arab Emirates, and Yemen), and five countries in Central Asia (Kazakhstan, Kyrgyzstan, Tajikistan, Turkmenistan, and Uzbekistan).[4]

We calculate the number of Internet users for each country by collecting statistics of national populations from the World Bank and Internet penetration rate from the International Telecommunication Union. As of 2016, Indonesia was the third-largest country in Asia, with a population of 261 million and an Internet penetration rate of 20.4%. This implies a total number of 53 million Internet users, which is a country's potential market size for piracy consumption. The number of Internet users in Indonesia is also larger than that in other Southeast Asian countries: Vietnam has 49 million Internet users, the Philippines has 45 million, Thailand has 29 million and Malaysia has 21 million.

4.2. Netflix Titles

We focus on Netflix titles that were available in Indonesia throughout the posttreatment period (January 27, 2016–June 16, 2016) to limit the scope of the study. We use the Wayback Machine on Finder.com's web pages to retrieve a list of 703 titles, including both movies and TV shows, available on Netflix in Indonesia in January 2016. Because Netflix frequently updates its catalog, not all 703 titles may have

[4] Netflix was also available in Iran, but Google Ads, which we use to collect search data, is not available in Iran (Prabhu 2011).

been available throughout the entire posttreatment period. As the Wayback Machine does not provide a full snapshot of Finder.com's Netflix title lists in Indonesia after June 2016, we instead collect Netflix titles that were available in Indonesia in March 2018 from an alternative source, JustWatch (2189 titles).[5] We find that 304 of the 703 titles remained in Netflix's catalog in Indonesia as of March 2018. Online Appendix A provides the names of all 304 Netflix titles. We assume that a title was available throughout the posttreatment period if it appeared in Netflix's catalog in both January 2016 and March 2018. For these 304 titles, approximately one-third (109) are TV shows and two-thirds (195) are movies, and 16% of the titles are Netflix originals (shows exclusively distributed by Netflix).[6]

We further check the availability of the 304 titles in the control countries. While similar retrieval of Netflix titles across all 40 countries proved untenable, we do recover the list of titles for a small set of countries neighboring Indonesia (India, the Philippines, Malaysia, and Vietnam) using the same method as for Indonesia. We find that all 304 titles were available in at least one of these four countries, and therefore focus on these titles in the main analysis.[7]

4.3. Data on Piracy Search

Previous marketing and economics research has shown that keyword search frequency on online search engines serves as a suitable proxy for (or a strong predictor of) consumer demand in contexts such as the automotive market (Hu et al. 2014), movies and TV shows (Liu et al. 2016), news media (Lambrecht and Misra 2017), recreational cannabis (Wang et al. 2019), and video games (Xiong and Bharadwaj 2014). Studies in psychology, public heath, political science have also found that Google search data are highly correlated with a variety of behaviors, such as suicides (Ma-Kellams et al. 2016), smoking cessation (Ayers et al. 2014), voting decisions (Stephens-Davidowitz 2014), and drug-related crimes (Gamma et al. 2016). Following previous research, we use consumer search for piracy-related queries on Google as a

[5] We also used the Wayback Machine on JustWatch (https://www.justwatch.com/id/provider/netflix) to access Indonesia's Netflix catalog. The earliest record of JustWatch on the Wayback Machine was in June 2017. However, the Wayback Machine only saved a subset of Netflix titles (60) in Indonesia.
[6] We treat TV shows with multiple seasons as one title.
[7] We show the robustness of the findings to the use of all 703 titles in Section 6.4.

proxy for piracy demand. Specifically, we use Google Ads' (formerly Google Adwords) keyword planner to collect search data for each of the 304 Netflix titles in each country (the 40 control countries and Indonesia). Google was the dominant search engine in Indonesia, accounting for 96.5% of all search in 2016 (Statcounter 2018). Google Ads reports monthly country-specific search volume for keywords. At the time of our study, we were able to use Google Ads to collect search data from as early as October 2014 because Google Ads' Keyword Planner only reports data for the past four years.

We use Google Correlate and Google Trends to identify queries that consumers most frequently use when trying to illegally download or stream movies and TV shows. To capture search for both streaming piracy and methods requiring a download, such as torrents, for a title named X, we collect monthly search volume for five keywords using the exact match method in Google Ads: "X torrent," "watch X free," "X download," "X free," and "stream X free." We then aggregate the search volume across these five keywords as the monthly piracy search volume for each title–country combination from October 2014 to June 2016. In some situations, titles overlap with terms that are not specific to the show of interest. This occurs when the title, such as *The Fall,* is a phrase commonly used for another purpose, or that the title refers to other downloadable products, such as video games (*Star Trek*), songs (*Creep*) or music albums (*Utopia*). In these cases, we include additional words in the search keyword to ensure that we accurately measure piracy activity for the exact movie or TV show in Netflix's catalog. Specifically, we instead collect data for "The Fall series," "Star Trek movie," "Creep movie," and "Utopia series." Despite this collection filter, inspection of the search data indicated serious anomalies for two titles: *Catch Me If You Can* and *Piku*; thus, we dropped these two titles and focused on the remaining 302 titles in subsequent analyses. In Online Appendix B, we show the robustness of the findings to the inclusion of *Catch Me If You Can* and *Piku* in sampled titles.

During the data period (October 2014–June 2016), the monthly piracy search volume of an individual title in Indonesia had a mean of 52.5 and a maximum of 4,000 searches, while the 40 control countries had a mean of 15.2 and a maximum of 5,800 searches per title. This suggests that the mean of monthly piracy search volume across all 302 titles is $52.5 \times 302 = 15{,}855$ in Indonesia and $15.2 \times 302 = 4{,}590$

in the 40 control countries. Four of the top 10 titles with the highest piracy search volume in Indonesia overlap with the highest search volume in the 40 control countries (*The Lord of the Rings: The Fellowship of the Ring*, *How to Train Your Dragon*, *Arrow*, and *Gravity*), suggesting some discrepancy in the piracy search interest between Indonesian consumers and representative consumers from the 40 control countries.

We also use Google Ads to collect several additional variables related to consumer search. These variables include the monthly search volume of a title-associated keyword in each country, the monthly search volume of the keyword "Netflix," and the monthly search volume of keywords related to piracy ("torrent," "movie torrent," "film torrent," "TV show torrent," and "TV series torrent"). To gauge the search interest of the Netflix titles in the control countries, for each title we calculate the number of control countries that have positive search volume of title-associated keywords during the data period. Across the 302 titles, each title, on average, has positive search volume in 39 control countries (median = 40), suggesting the popularity of these titles in the control countries.

To ensure that piracy search is a reasonable proxy for piracy demand, we collect additional data on visits to piracy sites related to film or TV from MUSO, a leading piracy-tracking company. We check the correlation of monthly country-specific piracy search volume from Google Ads with the piracy visit data from MUSO. Here, piracy search volume refers to the total search volume of piracy-related keywords used in the study ("torrent," "download," "watch free," and "stream free"). As MUSO data are at the daily level, we aggregate the piracy visit in each country to the monthly level to be comparable with the search data. This correlation check is based on data from January 2017 (the first month in MUSO's database) to October 2019 (34 months) in all 41 Asian countries, which results in 1,394 observations in total. Piracy search volume is strongly correlated with piracy visits related to film or TV ($r = 0.651$). The correlation between search volume and piracy visits related to film or TV is also strong in Indonesia ($r = 0.587$). These correlations provide empirical support for the use of piracy search volume as a proxy for piracy demand. Unfortunately, MUSO's piracy visit data cannot be used as the main dependent variable in this research because MUSO's data begin in January 2017, whereas the posttreatment period in this study ends in June 2016.

5. Empirical Analysis

We conduct two sets of empirical analyses to examine the effect of Netflix's failure to launch and subsequent unavailability in Indonesia on consumer search for piracy. We first present a DiD model, and then relax the identifying assumptions of a DiD model by employing a synthetic control method. We proceed by discussing the suitability of the synthetic control method to this empirical context, highlighting identifying assumptions, and finally presenting estimation results.

5.1. DiD Analysis

To examine the effect of Netflix's unavailability in Indonesia on piracy search, we first consider a DiD model in which we use the 40 other Asian countries where Netflix simultaneously entered as individual control markets. We consider the following specification:

$$y_{it} = \beta Event_t + \gamma Event_t \times Indonesia_i + \alpha_i + \epsilon_{it}, \quad (1)$$

where y_{it} represents aggregate normalized piracy search volume in country i ($i \in [1, \dots, 41]$) at month t ($t \in [-15, \dots -1, 1, \dots 5]$). We exclude observations in January 2016 ($t = 0$) to be consistent with the definition of pretreatment period from October 2014 to December 2015.

We calculate the normalized piracy search volume y_{it} in two steps. First, we aggregate the piracy search volume for each title k, denoted by y_{ikt}, across the 302 titles to obtain country- and month-specific raw piracy search volume denoted by y_{it}^R. Second, we normalize the piracy search volume by dividing y_{it}^R by the level at the month of intervention ($t = 0$). In other words, $y_{it} = \frac{y_{it}^R}{y_{i0}^R}$, where $y_{it}^R = \sum_k y_{ikt}$. As the raw piracy search volume is generally greater in countries with larger populations such as India and Indonesia, the normalized value allows the dependent variable and, thus, the estimated coefficient (effect size) to be comparable across countries.[8] For ease of exposition, we refer to y_{it} as the “piracy search volume” hereinafter.

In Equation (1), $Event_t$ is an indicator variable that takes the value of 1 for the posttreatment period and 0 otherwise; α_i stands for country fixed effects; and β captures the overall change in piracy search, across all countries, after the treatment (Netflix’s failure to launch in Indonesia). The main parameter of interest is γ, which captures the change of piracy search in Indonesia after the treatment relative to that in the control countries. A positive γ would indicate that Netflix’s failure to launch in Indonesia led to an increase in piracy search there compared with the control countries, averaged across the five posttreatment months.

We present the DiD estimation results in Table 1. Given the small number of treated units (one in this setting), the typical asymptotic inference based on a large number of policy changes tends to bias the estimates on standard errors (Conley and Taber 2011). We therefore follow the literature to report the *p*-value of γ from permutation inference, in addition to the *p*-value from robust standard error. The results show that Netflix’s unavailability led to a 17.9% increase in piracy search in Indonesia relative to the control countries ($\gamma = 0.179$, $p < 0.10$). We show in Online Appendix C that alternative variations of the DiD model lead to qualitatively similar results.

< Insert Table 1 about here >

A critical identifying assumption for the DiD method is that, in the absence of intervention, control and treatment groups will have parallel trends in average outcomes during the pretreatment period. If the parallel trends assumption fails, the control group will not be a good counterfactual for Indonesia, and therefore the DiD estimates will be biased. Although the parallel trends assumption is not directly testable, researchers usually have more confidence in its validity when they find that the average outcomes of the treated and control units follow a similar path in pretreatment periods. We follow

[8] Without normalization, the scales will not be comparable across countries. For example, the 1,591 increase in monthly piracy search volume before and after the treatment is a moderate change for Indonesia (mean = 15,844), but a gigantic change for a smaller country such as Bhutan (mean = 86.2).

Danaher et al. (2010) and examine this pattern by plotting the predicted monthly piracy search volume in Indonesia and the control countries using the following model specification:

$$y_{it} = \sum_{t=-15}^{t=5} \beta_t Month_t + \sum_{t=-15}^{t=5} \gamma_t Month_t \times Indonesia_i + \alpha_i + \epsilon_{it}, \quad (2)$$

where $Month_t$ is an indicator variable for month *t* and the other variables are the same as in Equation (1). If the parallel trends assumption holds, γ_t will be equal to 0 for each pretreatment month. We plot the predicted monthly piracy search volume for Indonesia and the control countries in Figure 2, where piracy levels in Indonesia are given by $\beta_t + \gamma_t + \bar{y}_{it}(T)$ and piracy levels in control countries are $\beta_t + \bar{y}_{it}(C)$. Here, $\bar{y}_{it}(T)$ and $\bar{y}_{it}(C)$ are the average baseline piracy searches during the pretreatment period for the treated and control countries. The patterns in Figure 2 do not strongly support the parallel trends assumption because the trend of piracy search in the control countries deviates from the trend in Indonesia before the treatment. We further test if $\gamma_t = 0$ for $t = -15, \ldots, -1$. Of the 15 tests, 13 are rejected at the 5% level. A Wald test of the null hypothesis that all $\{\gamma_t\}_{t=-15}^{t=-1}$ are jointly equal to 0 is also rejected at the 0.1% level.

< Insert Figure 2 about here >

The lack of strong evidence for a parallel trend in the DiD model using aggregate controls leaves two options. We can either identify one or a few selected countries from the 40 countries that fit Indonesia better before the treatment, or use a synthetic control method. We investigate the former option in Online Appendix C, where we provide additional model-free evidence of the treatment effect using individual control markets. However, this option of manually selecting control countries requires researchers to make ad-hoc assumptions. For example, at what level of fit do we decide if a country is appropriate for the control? Should we assign equal or different weights to those selected countries when forming the control? If nonequal weights are preferred, how should we determine the weights? These ad hoc assumptions rely on subjective criteria and therefore make the first option unappealing (Abadie et al. 2010). We therefore focus on the latter option, the synthetic control method.

5.2. Synthetic Control Method

The synthetic control method extends the conventional DiD framework by allowing the effect of unobserved confounders on the outcome to vary over time (Abadie and Gardeazabal 2003, Abadie et al. 2010). By using matching methods conditioned on pretreatment covariates and outcomes, the synthetic control method helps balance the effect of potential time-varying confounders between the treated and control groups (Xu 2017). Whereas the DiD analysis assigns equal weights to all control countries, the synthetic control method estimates weights for each of the 40 countries in a data-driven manner so that the resulting synthetic Indonesia best approximates the actual Indonesia on stated features during the pretreatment period. After constructing the synthetic control country, we calculate the treatment effect as the average gap between the predicted piracy search volume in the synthetic control and the actual piracy search volume in Indonesia during the posttreatment period.

5.2.1. Model. Following Abadie et al. (2010, 2015), we define the synthetic control country as a weighted average of the *J* countries in the control group. Let $i = 1$ represent the focal treated country (Indonesia) and $i \in [2, \dots, J+1]$ represent the potential control countries. The predicted outcome in the synthetic control is represented by $\sum_{i=2}^{i=J+1} W y_{it}$, where $W = (w_2, \dots, w_{J+1})$ is a $(J \times 1)$ vector of country-specific nonnegative weights ($w_i \in [0,1]$ and $\sum_{i=2}^{J+1} w_i = 1$). We select the optimal weights (W^*) to minimize the difference between the pretreatment characteristics of the treated country and the synthetic control during the pretreatment period. Let X_1 denote an $(M \times 1)$ vector of pretreatment characteristics for the treated country and X_0 denote the corresponding $(M \times J)$ matrix of pretreatment characteristics for the *J* control countries. Then, we obtain the optimal weights W^* by minimizing

$$\sum_{m=1}^{M} v_m (X_{1m} - X_{0m} W)^2, \tag{3}$$

where X_{1m} represents the value of m^{th} pretreatment characteristic of the treated country, X_{0m} is the corresponding vector of the same characteristic of the *J* control countries, and v_m is a weight measuring the relative importance of each pretreatment characteristic in matching the treated unit and the synthetic control. According to Abadie et al. (2010, 2015), a pretreatment characteristic with greater prediction power on the outcome should be assigned with a larger v_m. Specifically, v_m can be chosen by minimizing the mean squared prediction error (MSPE) of the outcome variable in the pretreatment period.

Given the optimal weights (W^*) derived from minimizing Equation (3), the synthetic control estimator for the treatment effect in posttreatment period *t* is given by

$$\hat{\alpha}_{1t} = y_{1t} - \sum_{i=2}^{i=J+1} w_i^* y_{it}, \tag{4}$$

where $\hat{\alpha}_{1t}$ is the gap between the treated unit and the synthetic control.

5.2.2. Matching Characteristics. Abadie et al. (2010, 2015) recommend using predictors of posttreatment outcomes (piracy search volume of Netflix titles) as pretreatment characteristics. We therefore include the following country-specific variables as pretreatment characteristics for constructing the synthetic control: *title search volume* (monthly search volume for all sampled Netflix titles), *interest in Netflix* (monthly search volume for the keyword "Netflix"), *interest in general piracy* (monthly search volume for piracy-related keywords mentioned in Section 4.3), *interest in competitors* (monthly search volume for keywords of Netflix's major competitors[9]), and *Internet users* (annual). Following Abadie et al. (2010, 2015), we also include the pretreatment outcome (*piracy search volume*) in X_0 and X_1.[10]

5.2.3. Identifying Assumptions. For the synthetic control method to yield valid results, four identifying assumptions must be met. First, the treated and the synthetic control country should exhibit similar patterns in the pretreatment period (Abadie et al. 2010). Subsequently, we provide evidence that the gap in piracy search volume between Indonesia and the synthetic control country is close to zero before the treatment.

The second assumption is that only the treated unit (Indonesia) undergoes the treatment – Netflix's failure to launch – and any control country did not. An extensive search confirms that none of the 40

[9] We collect the search volume data for the following keywords of Netflix's competitors: "Amazon Prime," "Catchplay," "Fimplus," "Genflex," "HOOQ," "Hulu," "iflix," "Tribe," "Viki," "Viu," "Voot," and "YuppTV."
[10] We check the robustness of the results to adding additional economic factors (gross domestic product, employment rate, and inflation rate) to pretreatment characteristics. The inclusion of these factors led to a worse match of the pretreatment period (as indicated by larger MSPE). We therefore focus on a parsimonious model without these economic factors.

control countries in Asia experienced Netflix unavailability during the intervention period (February 2016–June 2016).

Third, according to Abadie et al. (2010), the treatment that occurred in the focal country should not affect the outcome in the control countries, and vice versa. In other words, there should be no spillover effects of the treatment (or lack of the treatment). The spillover effect might occur if Indonesians used Virtual Private Networks (VPNs) to access Netflix through the service in control countries after the block of Netflix in the domestic market. However, cross-country access was unlikely during the period of analysis because, in January 2016, Netflix expended substantial effort to prevent customers from bypassing country lines using unblocking tools such as VPNs (Verge 2016). While we are unable to fully verify this assumption, there is substantial evidence that Netflix's failure to launch in Indonesia had little influence on piracy demand in other countries because of language, cultural, and regulatory differences, as well as Netflix's increasing emphasis on setting virtual country restrictions. The spillover effect can also occur if Indonesians tend to read news from foreign countries, which enables the news about Netflix and its content in these foreign countries to affect Indonesians' piracy behavior through WOM. We investigate this issue in Online Appendix D and provide evidence that mitigates the concerns about spillovers of WOM.

The fourth assumption requires that there are no alternative changes to either the treated or control countries during the posttreatment period. This implies that, at a minimum, no other alternative OTT service providers should enter during this time period. If alternative events occur, the estimates would actually measure the combined effects of the focal intervention and these alternative ones. As discussed in Section 3.2, we choose a posttreatment window during which there were no significant events that might affect piracy in Indonesia, so this assumption holds. In Section 5.3, we further verify this assumption for the countries that contribute to the formation of the synthetic control country. The price charged by Netflix may also be heterogenous across countries, although as shown in Online Appendix D, that does not appear to be the case.

5.3. Results

We construct the synthetic control country for Indonesia from a collection of 40 Asian countries by matching pretreatment characteristics from October 2014 to December 2015 (15 months). Table 2 shows the full list of potential control countries and associated weights (w_i^*) in the synthetic Indonesia. The weighting algorithm identifies a synthetic control country that puts substantial weights on four countries: Thailand (0.43), Palestine (0.38), the Philippines (0.12), and India (0.08). These countries appear to be reasonable proxies for Indonesia. For example, Thailand and the Philippines are geographic neighbors of Indonesia. In addition, Indonesia has a large Muslim population, which aligns with the characteristics of Palestine. While these control countries appear to have high external validity, there exists other countries, such as Malaysia, which are not members of this group. In Online Appendix D, we provide further detail on why some countries that seem similar to Indonesia, may not be selected by the synthetic control method. Finally, we also search for notable demand shocks in the four control countries during the posttreatment period as an additional check of the fourth assumption in Section 5.2.3.

< Insert Table 2 about here >

Table 3 presents the means of pretreatment characteristics for Indonesia, the synthetic control country, and the 40 control countries. As this table shows, the synthetic control country is more similar to Indonesia than the control with equal weights – which is the control used in the DiD analysis. For example, before the intervention, the total search volume of Netflix titles in an average control country was only 43% of the level in Indonesia. By contrast, the search volume of Netflix titles in the synthetic Indonesia achieves a much better match (94%).

< Insert Table 3 and Figure 3 about here >

Figure 3 depicts the trajectory of piracy search volume of Netflix titles in Indonesia (solid) and its synthetic counterpart (dashed) over the period of analysis. First, the synthetic control country fits Indonesia reasonably well during the pretreatment period ($t < 0$), providing support for the first assumption in Section 5.2.3. Second, there is a statistically significant downward trend in piracy search volume during the pretreatment period (Indonesia: slope = –0.021, p = 0.007; synthetic control country: slope = –0.021, p = 0.001). However, after Netflix's entry into the control countries at $t = 0$, the piracy search volume in the synthetic control country moves further downward and is always below the piracy search volume in Indonesia, which suggests an increase in piracy search volume in Indonesia relative to the synthetic control country after the treatment. Such a divergence in piracy search volume between Indonesia and the synthetic control country is also apparent in the difference in trends after the treatment. The downward trend of piracy search volume in Indonesia is similar before and after the treatment, although the posttreatment slope is not statistically significant (slope = –0.021, p = 0.541). The downward trend in piracy search volume in the synthetic control country is steeper after the treatment (slope = –0.057, p = 0.003) than beforehand.

The gap plot in Figure 4 illustrates the magnitude of the effect of Netflix's unavailability in Indonesia on piracy search. The relatively small gap in the first month after the treatment ($t = 1$) suggests that the effect is not strong initially. However, from March 2016 ($t = 2$) onward, the effect becomes more pronounced, perhaps because consumers came to realize that the block was not temporary and therefore began seeking piracy to substitute the OTT service. The average gap in piracy search volume between the actual and the synthetic Indonesia totals 0.197 over the five months following Indonesia's Netflix block, which suggests that Netflix's unavailability is associated with a 19.7% increase in piracy search in Indonesia relative to the other 40 countries where Netflix entered and remained available. This effect size is comparable to the 20% decrease in piracy of ABC's content after that content was added to Hulu (Danaher et al. 2015). This comparison is notable despite substantial differences between Hulu and Netflix at the time of each study; Hulu was a free service with only licensed content in 2008, whereas Netflix in 2016 was a paid service with both licensed and original content. In contrast, Danaher et al. (2010) found that the removal of NBC shows from iTunes led to an 11.4% increase in demand for pirated content. This lower magnitude might have occurred because iTunes is merely an a la carte service.

There are at least two possibilities that might lead to an overestimation of the treatment effect. One, if the three-week availability of Netflix in Indonesia in January 2016 generated some demand for content, the gap estimates using data from the five posttreatment months can be a combined effect of Netflix's unavailability from February to June and the short-term operation of Netflix in January. Second, the spike in piracy search in Indonesia in March 2016 may be an outlier, the inclusion of which may result in an overestimated treatment effect. We consider these two possibilities in Online Appendix D and present empirical evidence that neither of them is likely to hold, which suggests that the estimated treatment effect is unlikely to be biased.

< Insert Figure 4 about here >

We follow the synthetic control literature by using permutation inference to assess the significance of treatment effect (Abadie et al. 2010, 2015, Tirunillai and Tellis 2017).[11] For each country j in the control group ($j = 2, \ldots, 41$), we iteratively estimate the average posttreatment gap in piracy search volume relative to that of the synthetic control of this country. We then use the distribution of these placebo treatment effects to measure the significance of the actual treatment effect.

Two measures are often used to evaluate the significance of the treatment effect obtained from the synthetic control method. The first measure is the ratio of post-/pretreatment MSPE obtained from placebo runs across countries (Abadie et al. 2010, 2015, Tirunillai and Tellis 2017). The main advantage of this method is that it does not require choosing a cutoff to determine the inclusion of well-fit placebo tests. In other words, it uses information from all placebo runs. If the post-/pretreatment MSPE ratio is greater for Indonesia than for the other countries, we can confidently reject the null hypothesis that Netflix's failure to launch in Indonesia has no effect on piracy search. The pretreatment MSPE of piracy search in Indonesia is 0.003, while the mean and median of pretreatment MSPE among the 40 other countries are 0.072 and 0.012. As Figure 5 shows, Indonesia has a greater post-/pretreatment MSPE ratio than any of the other 40 countries; thus, the probability of obtaining a post-/pretreatment MSPE ratio as large as Indonesia's is 1/41 = 0.024, if the event randomly occurred in one of the 41 Asian countries.

< Insert Figure 5 about here >

The second measure is to simply compare the size of gaps across all countries. The downside of this test is that it may be biased by countries lacking a suitable synthetic control, which typically have a poor

[11] Recent studies such as Xu 2017 and Li 2019 have developed inferential theories for extended versions of the synthetic control method. An inferential theory for the standard synthetic control method is still lacking.

pretreatment fit. Figure 6 shows the results from the placebo tests. The gray lines in panel (a) depict the estimated gaps for each of the placebo tests of the 40 control countries, and the black line represents the estimated gap for Indonesia. The figure suggests that, for many countries, the synthetic control method does not provide a good fit for piracy search during the pretreatment period. As Abadie et al. (2010) note, placebo tests with poor pretreatment fit do not provide information to gauge the potential randomness of observing a large posttreatment gap from a country with a good fit before the intervention. We follow Abadie et al. (2010) and exclude countries that have a pretreatment MSPE beyond a certain level.

We replot the placebo tests in panels (b) and (c) of Figure 6 by excluding countries with a pretreatment MSPE of more than 10 times and two times the MSPE of Indonesia. Among the 31 countries remaining in panel (b), the average posttreatment gap of Indonesia is the third-highest (after Myanmar and Nepal), suggesting a probability of 3/31 = 0.097 of observing a gap of the magnitude that is equal to or greater than the gap for Indonesia under a random assignment of the treatment in the data. The significance of the positive gap for Indonesia becomes more visible in panel (c) when we lower the cutoff on pretreatment fit to twice that of the MSPE of Indonesia. The average gap for Indonesia is the highest among the 12 countries, suggesting a 1/12 = 0.083 chance of observing the same gap as Indonesia's if the treatment were randomly assigned to a country.

< Insert Figure 6 about here >

5.4. Heterogeneous Effects of the Treatment

5.4.1. Moderating Role of Content Exclusivity. We examine the moderating role of content exclusivity to better understand whether the main positive treatment effect of Netflix's unavailability in Indonesia on piracy search is driven solely by the substitution effect, or by a combination of the substitution effect and the market expansion effect. If the main effect is driven solely by substitution, we expect the positive treatment effect to be stronger for Netflix originals. Unlike nonoriginal content, which is available from multiple legitimate sources, original content is exclusively broadcast on Netflix. Therefore, it is impossible for consumers to find the same show from other legitimate sources if Netflix becomes unavailable. This argument suggests a higher level of substitution between the OTT service and piracy for original content than for nonoriginal content.[12] Let θ_O^S and θ_N^S denote the positive substitution effect of Netflix's unavailability in Indonesia on piracy search for original and nonoriginal content, respectively. Given the previous reasoning, we expect $\theta_O^S > \theta_N^S > 0$, where the superscript "S" stands for substitution, the subscript "O" stands for original content, and the subscript "N" stands for nonoriginal content.

Theoretically, it is also possible that an OTT service increases demand for piracy because of the increase in WOM and promotion associated with the introduction of the OTT service, which may drive consumers to seek out the same content provided by the OTT platform through piracy. Since such a market expansion effect is usually more pronounced for the introduction of new products than existing products (Chen et al. 2005), we expect the market expansion mechanism to lead to a more negative effect of Netflix's unavailability in Indonesia on piracy search for original content than nonoriginal content. Formally, we expect $\theta_O^E < \theta_N^E < 0$, where θ_O^E and θ_N^E denote the potential negative market expansion effects of Netflix's unavailability in Indonesia on piracy search for original and nonoriginal content, respectively, and the superscript "E" stands for expansion.

This discussion suggests that if only a substitution effect is present, the net effect of the treatment for original content will be stronger than that for nonoriginal content ($\Delta\theta = \Delta\theta^S = \theta_O^S - \theta_N^S > 0$). However, if both effects exist, the net effect for Netflix originals will be either positive or negative, depending on the relative strength of the two effects. Let $\theta_O = \theta_O^S + \theta_O^E$ ($\theta_N = \theta_N^S + \theta_N^E$) denote the net effect for original (nonoriginal) content. When both substitution and market expansion effects exist, the difference in the net effect of treatment between original and nonoriginal content is the same as the difference between the change in piracy substitution and the change in piracy expansion: $\Delta\theta = \theta_O - \theta_N = \Delta\theta^S - \Delta\theta^E$, where $\Delta\theta^S = \theta_O^S - \theta_N^S > 0$ and $\Delta\theta^E = \theta_N^E - \theta_O^E > 0$. If the magnitude of the market expansion effect for original content relative to nonoriginal content ($\Delta\theta^E$) outweighs the magnitude of the substitution effect for original content relative to nonoriginal content ($\Delta\theta^S$), we expect to observe a weaker net effect of treatment on piracy search for original content than nonoriginal content ($\Delta\theta < 0$).

[12] We provide more details and empirical support for this argument in Online Appendix C.

Calculation of the effect of Netflix's unavailability in Indonesia on piracy search for original and nonoriginal content can be done in at least two ways. The first is to use one synthetic Indonesia as the control country for all titles (in this case, the synthetic Indonesia is the same as the one created for the main analysis in Section 5.3). Because the piracy search volume for Netflix originals is not necessarily matched between the actual and synthetic Indonesia before the treatment, we cannot use the average posttreatment gap as an estimate of the treatment effect directly. Instead, we follow the idea of DiD to use the change in the average posttreatment gap between the actual and synthetic Indonesia relative to the average pretreatment gap to estimate the treatment effect. We find an effect size of 0.048 for original content and 0.241 for nonoriginal content. The second way is to apply the synthetic control method to aggregate piracy search volume of 49 Netflix originals and 253 nonoriginals, separately. We find that Netflix originals have an average posttreatment gap in piracy search of 0.063. However, 10 other countries have a higher post-/pretreatment MSPE ratio than Indonesia, implying that the effect for Netflix originals is nonsignificant because of a p-value of 11/41 = 0.27. For nonoriginal titles, the average posttreatment gap estimate is 0.161, and Indonesia has the third-highest post-/pretreatment MSPE ratio, suggesting a p-value of 3/41 = 0.073. The results from both methods indicate that the net effect of Netflix's unavailability in Indonesia on piracy search is smaller for original content than for nonoriginal content ($\Delta\theta < 0$), which is consistent with the coexistence of a substitution effect and a market expansion effect rather than the existence of a substitution effect alone. We provide additional evidence for the market expansion effect and rule out an alternative explanation for the smaller effect for original content due to the lack of piracy availability in Online Appendix E.

5.4.2. Moderating Role of Dialogue Orientation. The majority of Netflix titles (292 of 302) are not in the primary local languages of any of the 41 Asian countries, according to IMDb. Furthermore, 290 of 292 foreign titles are in English.[13] Less dialogue-oriented titles are likely to be more appealing to Asian consumers because of lower language barriers; therefore, we expect a stronger substitution effect of the

[13] One title is in Spanish (*Club de Cuervos*) and one title is in French (*Wakfu*). For the remaining 290 foreign titles, 10 are in dual languages, one of which is English, and 280 are in English only.

availability of OTT service on piracy search for less dialogue-oriented titles. In other words, we expect the positive effect of Netflix's unavailability on piracy search in Indonesia relative to the synthetic control country to be greater for less dialogue-oriented titles.

We measure the degree of dialogue orientation using the average number of words per minute for each title. We collect the script data from a U.K.-based script database[14] and the length of each title from IMDb. The script data are available for 228 titles. The average number of words per minute has a mean of 86.9, a median of 82.1, and a range from 12.1 (*Halo 4: Forward unto Dawn*) to 174.6 (*The Fluffy Movie*). To test the moderating effect of dialogue orientation, we apply a median split, a three-way split, and a four-way split to the 228 titles, based on the degree of dialogue orientation, and then estimate the treatment effect for each group of titles using the same methods as in Section 5.4.1. Table 4 presents the results. Under a median split and the DiD-type method, Netflix's unavailability in Indonesia leads to a 27.4% increase in piracy search for titles with a low degree of dialogue orientation and a 9.7% increase in piracy search for titles with a high degree of dialogue orientation relative to the synthetic control country. The finding of the greater treatment effect for less dialogue-oriented titles is consistent with the expectation and is robust to alternative ways of classifying dialogue orientation (three-way and four-way splits) and an alternative estimation method (using separate synthetic controls).

< Insert Table 4 about here >

6. Robustness Checks

6.1. Varying the Number of Countries Used in the Synthetic Control

We check the robustness of the findings to the number of countries used in the formation of the synthetic control country. As Abadie et al. (2015) note, researchers typically favor a sparse set of synthetic control units because of the high interpretability of characteristics and outcomes between the focal unit and each of these control units. However, using fewer units in the synthetic control method may result in a lower pretreatment fit between the treated unit and the synthetic control. We explore the sensitivity of the

[14] http://SpringfieldSpringfield.co.uk. For TV shows with multiple episodes, we measure the dialogue orientation on the basis of the first episode.

pretreatment fit and our finding of the positive posttreatment gap in piracy search between Indonesia and the synthetic Indonesia to the number of countries that contribute to the synthetic Indonesia.

Recall that the synthetic Indonesia in the main analysis is a combination of, in decreasing importance, Thailand, Palestine, the Philippines, and India. Following Abadie et al. (2015), we sequentially decrease the number of countries used to construct the synthetic control from four to one. Table 5 reports the countries and weights for the sparse synthetic controls. Thailand is generally the largest contributor to the synthetic Indonesia, except when the number of control countries is three, when Palestine has the top weight. Philippines and India are the third and fourth contributors, respectively, in terms of their synthetic control weights. Figure 7 shows the piracy search path and gap for Indonesia, as well as the sparse synthetic controls with $l = 3,2,1$ countries included in the control group. Comparing Figure 7 with Figures 3 and 4 suggests that the sparse control with $l = 3, 2$ provides a similar pattern to the baseline result; there is both a good pretreatment fit and a significant gap in piracy search between Indonesia and the sparse synthetic control when $l = 3,2$. Similar to Abadie et al. (2015), the pretreatment fit is less than ideal when using only one country (Thailand) in the control set, which highlights the potential benefits of using a weighted combination of countries rather than a single country as the control unit.

< Insert Table 5 and Figure 7 about here >

6.2. Alternative Choices of Posttreatment Periods

We selected the posttreatment period to be from February 2016 to June 2016, during which other OTT service providers were not available in Indonesia. The five posttreatment months allows us to examine only the short-term effect of the treatment in this research. This selection provided the longest window during which there was no significant confound from other possible interventions. To ensure that the main findings are not driven by the choice of posttreatment period, we consider the average gap estimates and associated p-values from alternative posttreatment windows (see Table 6). Consistent with Figure 4, Indonesia's Netflix block did not have a substantial effect on piracy search during the first month (February 2016) after the intervention. The effect size of using a three-month posttreatment period (0.208) appears to be similar to the results of using a five-month window as in the main analyses. The effect estimates from a three-month posttreatment window are also significant in that Indonesia has the highest post-/pretreatment ratio among 41 countries based on placebo runs. These results provide evidence for the robustness of the findings to the posttreatment window.

Next, we explore how the effect of Netflix's unavailability in Indonesia on piracy search changes after the introduction of a local OTT service. To estimate this effect, we extend the posttreatment window to include periods after the entry of iflix in June 2016, and continuing to the entry of Netflix in April 2017. We do not collect data after April 2017, when Netflix was unblocked in Indonesia after its strategic partnership with Telkom. As expected, Table 6 shows that the positive effect of Netflix's unavailability in Indonesia on piracy search diminishes when including additional months in the posttreatment window. In particular, the average effect of Netflix's unavailability is small (0.039) and nonsignificant (p-value = 22/41 = 0.537) from July 2016 to April 2017, suggesting that the piracy search in Indonesia returned to the level in the synthetic control country when alternative OTT services became available in Indonesia. Notably, although we observe piracy search through April 2017 (15 months after the treatment), the entry of local OTT service providers such as iflix in June 2016 prevents us from separating the long-term effect of Netflix's unavailability in Indonesia and the effect of entry of local competitors when using posttreatment data from July 2016 to April 2017. The long-term effect – over five posttreatment months – reported in Table 6 should therefore be interpreted cautiously.

< Insert Table 6 about here >

6.3. Alternative Specifications of Piracy Search

The primary reason for using normalized piracy search volume as the dependent variable in the main analysis is that it allows us to directly compare the effect sizes across different countries. We examine the extent to which our findings are driven by this specification by considering alternative specifications of y_{it} in the synthetic control method.

As a robustness check, we use raw piracy search volume and log-transformed piracy search volume as outcome variables.[15] A good fit of pretreatment characteristics remains for both measures. For the effect size, the average posttreatment gap estimate from the model with raw piracy search volume is 2,974, which means that there is an average of 2,974 more searches of piracy-related terms about the 302 Netflix titles per month in Indonesia than in the synthetic control country. Given that the average raw piracy search volume in Indonesia was 16,920 in January 2016, this gap estimate suggests a 2974/16920 = 17.6% relative increase in piracy search from the baseline level in January 2016. For the model with log-transformed data, the average posttreatment gap estimate is 0.192, suggesting that the piracy search volume in Indonesia is, on average, 19.2% higher than the synthetic control country after the treatment. The effect sizes obtained from these two alternative models are similar to that from the normalized piracy search volume (19.7%), suggesting that the estimated treatment effect is not sensitive to the specification of outcome variable used in the synthetic control analyses.

6.4. Alternative Sampling of Netflix Titles

We present two robustness checks to the selection of Netflix titles, in addition to the robustness check to the inclusion of two titles with abnormal search patterns in Online Appendix B. As explained in Section 4.2, we sampled 304 titles appearing in Netflix's catalog in both January 2016 and March 2018 to avoid the inclusion of titles that Netflix might have removed during the posttreatment period. Nevertheless, anecdotal evidence shows that Netflix tends to sign multiyear contracts, based on Netflix's previous contracts with Disney (Sandoval 2012) and CW (Prudom 2016). It is possible that the 703 titles observed in Netflix's catalog in Indonesia in January 2016 were still available in June 2016. To ensure that findings from the main analysis are not subject to sample selection, we collect Google Ads data for the additional 399 Netflix titles that were available in Indonesia in January 2016 to conduct a robustness check. Because of the 48-month rolling window of data in Google Ads, the search data for the new 399 titles were only available after March 2015 at the time of data collection in May 2019, leaving us with nine months of

[15] For consistency, we take the log on search-related pretreatment characteristics in the model with log-transformed search data.

pretreatment data. Despite the relatively short pretreatment period, we apply the synthetic control method to the data of 701 titles (*Catch Me If You Can* and *Piku* were dropped because of the anomalies previously mentioned) and report detailed estimation results in Online Appendix F. We find that Netflix's unavailability in Indonesia led to a 22.4% increase in piracy search relative to the control countries. We also find that the effect size for nonoriginals (0.242) remains greater than that for originals (0.012). These results suggest that the main findings are robust to the inclusion of all titles.

The second robustness check pertains to the language of titles. If the majority of titles are in local languages, the supply shocks resulting from Netflix's entry might not be comparable between countries where most people speak these local languages and other countries. Given that most of the sampled titles (292 of 302) are not in the local languages of the 41 Asian countries, the introduction of Netflix should be comparable across countries. This observation also suggests that the market expansion effect is unlikely to be driven by the increase in piracy supply due to the improved convenience of creating piracy content from the existence of the same content on the OTT platform. When most titles are in foreign languages, the availability of an OTT service in a given country is unlikely to affect the piracy supply in that country so long as similar OTT services are available in other countries. As such, we explain the market expansion effect by the increase in WOM and promotion rather than the increase in piracy supply in this study. Despite the large proportion of foreign titles in this sample, 10 titles are still in local languages of the Asian countries. To ensure that the main findings are not driven by the data pattern associated with these 10 titles, we apply the synthetic control method using the 292 titles that are not in local languages of the Asian countries. We find qualitatively similar results and provide details in Online Appendix G.

7. Conclusion

This research presents new evidence for the effect of the availability of an OTT service on piracy search. Our identification strategy relies on Netflix's failure to launch in Indonesia in the wake of its global market expansion in 2016, which provides an exogenous shock to the availability of this service in Indonesia and therefore creates an opportunity for a natural experiment. Applying the synthetic control method to data from Indonesia and 40 Asian countries where Netflix entered and remained available, we find that Netflix's unavailability in Indonesia leads to a 19.7% increase in piracy search in Indonesia relative to the other countries. This result suggests an overall substitution between OTT services and piracy. Given the estimate of 160 million visits to piracy sites in 2017 (Muso 2017), our findings suggest that Netflix's global market expansion is responsible for a decrease of millions of visits to illegal sites.

We further investigate the differential effects of Netflix's unavailability in Indonesia on piracy search through two content characteristics. For content exclusivity, we find no significant treatment effect on searches for piracy of Netflix originals exclusively broadcast on Netflix but find a positive treatment effect on searches for piracy of nonoriginal content available on other legal channels. Such a data pattern is consistent with the coexistence of the substitution effect and the market expansion effect of OTT services on piracy rather than the substitution effect alone. For dialogue orientation, our results show that Netflix's unavailability in Indonesia leads to a greater increase in piracy search for less dialogue-oriented titles.

Our findings provide several implications for managers of OTT platforms and policy makers. OTT platforms concerned about piracy should be strategic in the way they fight it. Our results suggest that OTT platforms should target their limited antipiracy resources to combating piracy for content with exclusive distribution rights rather than content that is available on other legal channels. This suggestion seems to be in line with current methods of Netflix, which "sent out over a million takedown requests to Google alone since last year, and [is] currently looking to beef up its internal anti-piracy division" (Smith 2017) by actively hiring people focused on protecting Netflix's original content from piracy (Dassanayake 2017). Our finding on the moderating role of dialogue orientation suggests that OTT platforms should pay more attention to copyright protection for dialogue-heavy (vs. dialogue-light) titles, especially during launch in foreign markets.

Evidence of the effectiveness of government intervention on the supply of piracy in increasing legal consumption of media products is mixed, especially with regard to blocking individual websites. One of the most significant supply-side interventions, the shutdown of Megaupload in 2012, led to an increase in box office movie revenue for three major studios (Danaher and Smith 2014) but a decrease in box office revenue for an average movie (Peukert et al. 2017). Alternatively, simultaneous blocking orders directed at 19 major piracy sites in 2013 in the United Kingdom led to a meaningful reduction in total piracy and a 12% increase in the use of legal streaming sites (Danaher et al. 2019). The effectiveness of the shutdown of piracy sites on boosting legal consumption is therefore not guaranteed, unless a major coordinated action is taken. Our findings indicate that the introduction of OTT services is an effective way to discourage people from searching for piracy. While the 19.7% change in piracy search found in this study is not the same as a change in revenue, our finding of the substitution between OTT services and piracy suggests that the introduction of OTT services provides strong utility to consumers over piracy, which should ultimately lead to an increase in firm revenues. From a policy perspective, while punitive measures may reduce the supply of piracy, initiatives that spur the market entry of innovative, high-value media platforms may also produce a substantial decrease in piracy.

Despite the dominance of the substitution effect, our finding that the introduction of OTT services can generate more interest in piracy for some titles (market expansion effect) also provides important implications to content creators. The existence of the market expansion effect of an OTT service might result in lower revenues for content creators and reduced consumer welfare in the long run. This is mainly because the market expansion effect in the current period may sway consumers, who would not have been aware of certain titles, to incur the fixed cost of either learning to use BitTorrent or the fixed moral cost of illegal behavior. When the fixed cost of piracy is sunk in the current period, it may affect these consumers' preference for piracy over legal options in the future and therefore hurt the content creators' revenues in the long run. For example, a consumer who becomes aware of the first season of *Narcos* from market expansion might not yet be a candidate subscriber of Netflix at the time of entry. However, if this consumer watched the first season of *Narcos* on a piracy site, she might continue watching future seasons on illegal sites rather than on Netflix, negatively influencing Netflix's future value from this customer. If content creators are forward looking, such a detrimental effect on future revenues may motivate them to provide content at a suboptimal level in terms of quantity and quality, which in turn hurts consumer welfare. These are purely theoretical arguments, and an investigation of the long-term effect of Netflix's availability (or lack thereof) is beyond the scope of this research. Our discussion suggests that the market expansion effect could potentially harm the surplus of different stakeholders in the long run and therefore merits further investigation.

We note several limitations of this study. First, monthly data do not allow us to understand dynamics at a more detailed level, particularly during the period between when Netflix was introduced (January 6, 2016) and when Netflix was blocked (January 26, 2016). More granular data at daily level could uncover additional temporal patterns and provide a more accurate estimate of the treatment effect. Second, although we show that piracy search is highly correlated with visits to piracy sites, the dependent variable in this study references search rather than actual consumption of pirated content. There may exist situations in which the treatment effect on actual piracy behavior is different from our estimated effect. Third, while Telkom is far and away the market leader in Indonesia, it would be interesting to explore the extent to which individuals employ alternative telecommunication services to bypass Telkom's block. Given that Netflix is not completely blocked by all telecommunication firms in Indonesia, our estimated effect on piracy search in Indonesia relative to the control countries (19.7% increase) should serve as the lower bound of the true effect of the treatment. Finally, the lack of individual-level data hinders a deeper understanding of heterogeneous treatment effects across consumers, and may induce potential bias, which is particularly relevant for a country-level study. Despite these limitations, we hope this research stimulates further interest in exploring the effectiveness of antipiracy interventions.

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Figure 1. Interest in Netflix in Indonesia over Time

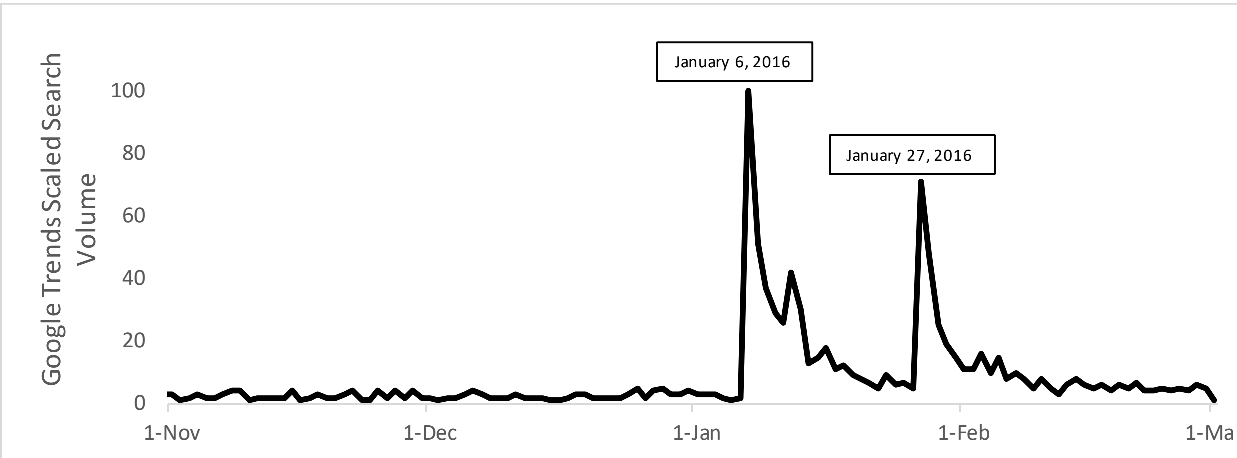


Figure 2. Predicted Piracy Search Volume between Indonesia and Control Countries

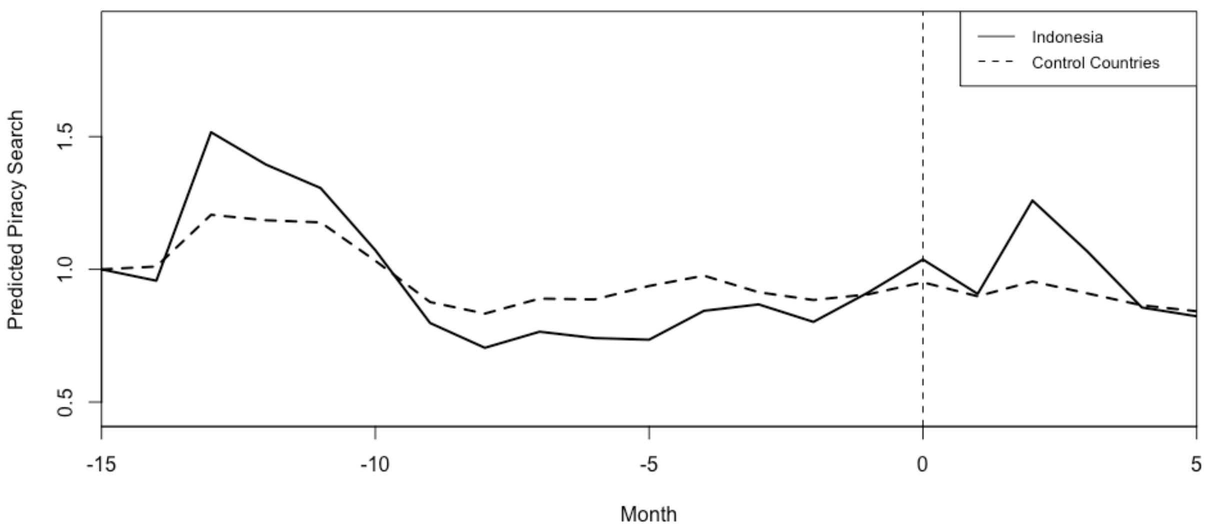


Figure 3. Trends of Piracy Search Volume: Indonesia vs. Synthetic Control Country

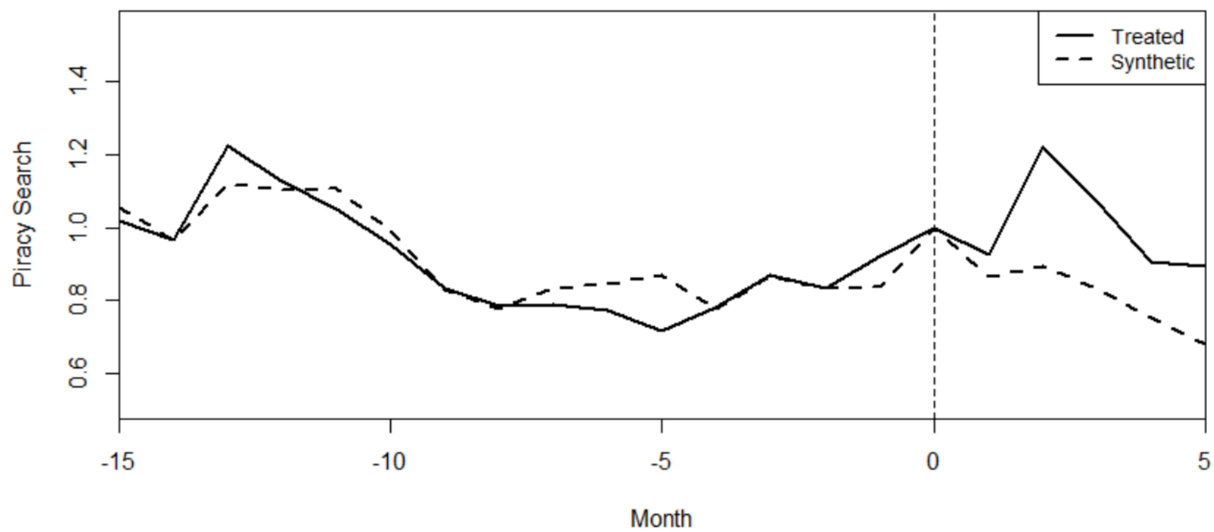


Figure 4. Gaps in Piracy Search Volume between Indonesia and Synthetic Control Country

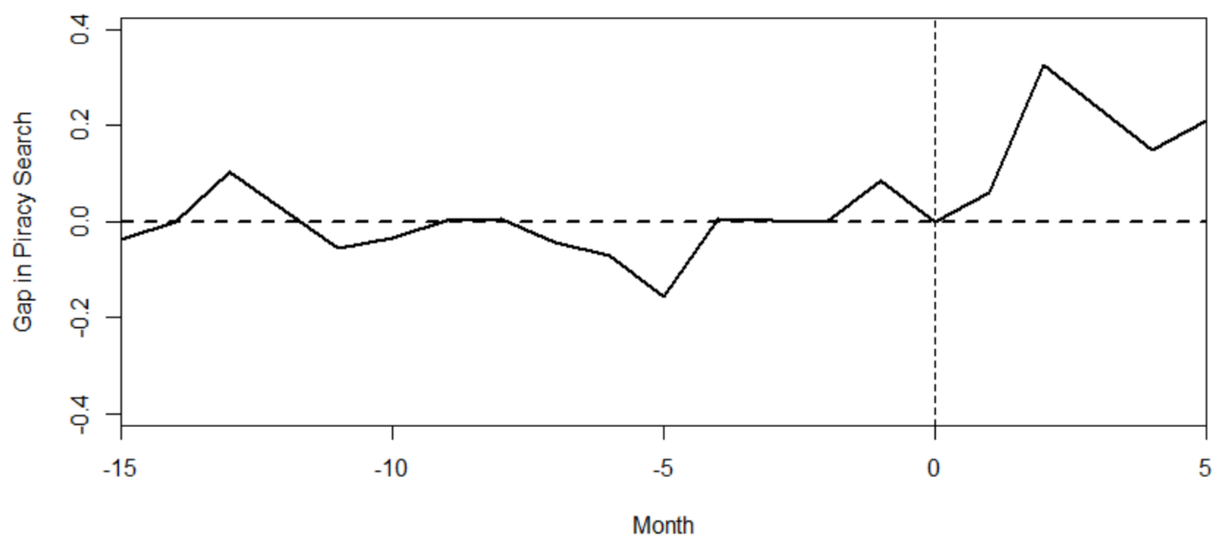


Figure 5. Ratio of Posttreatment MSPE to Pretreatment MSPE across All Countries

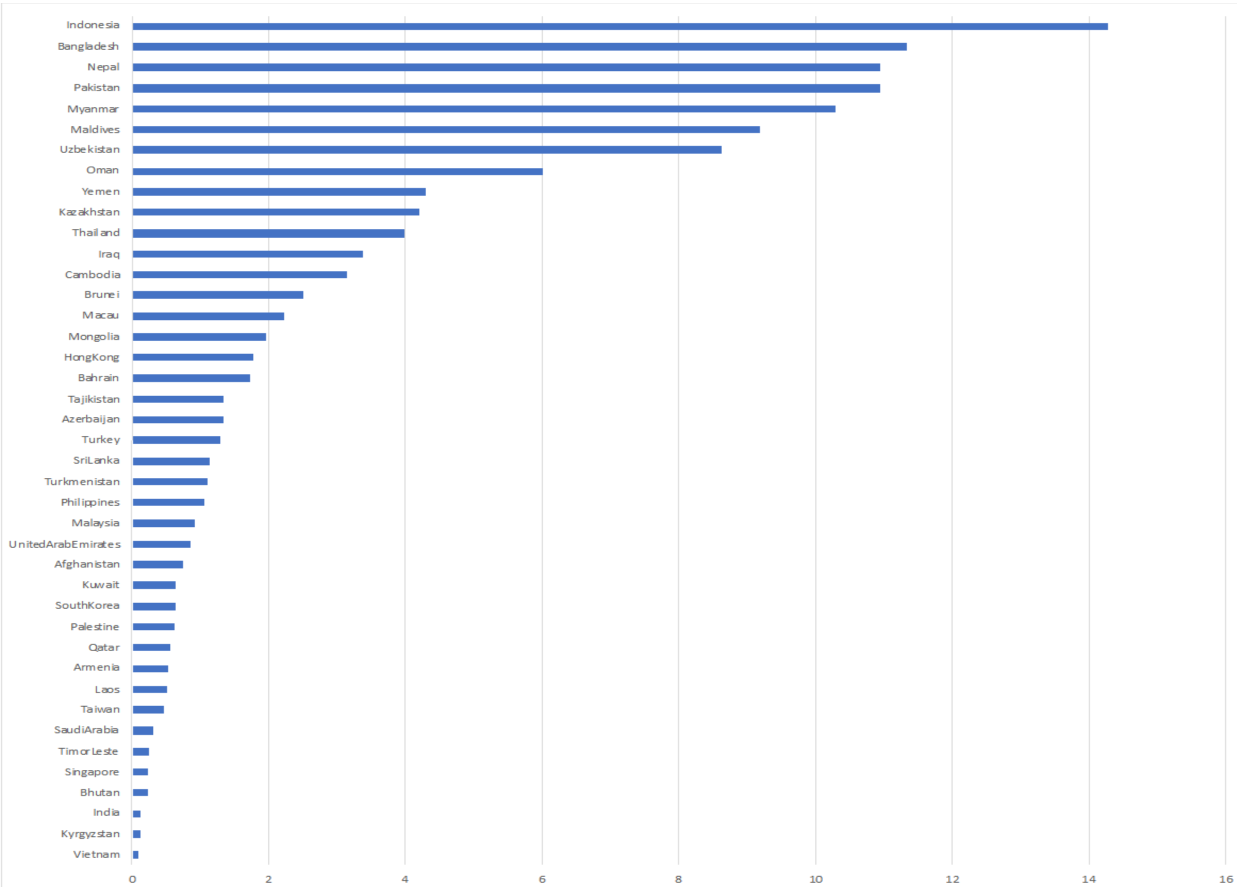
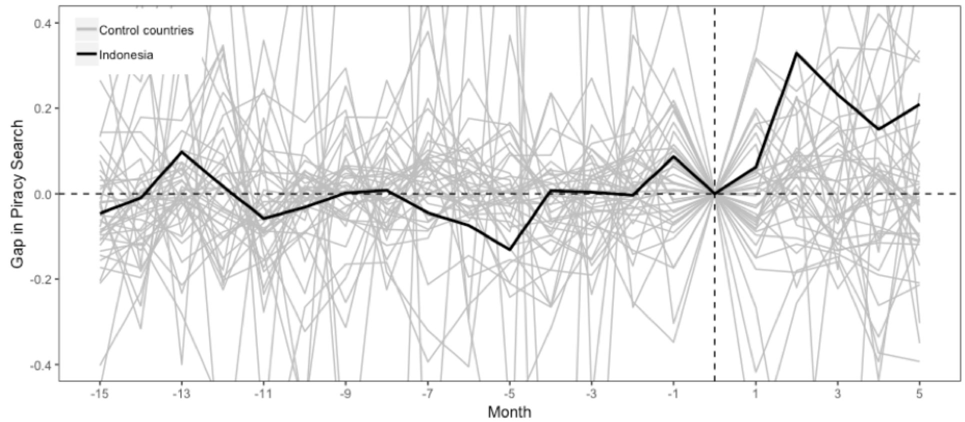
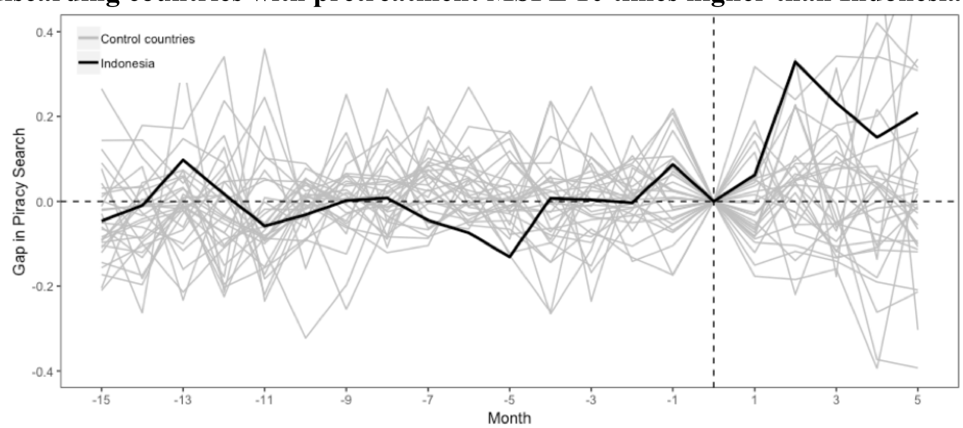


Figure 6. Placebo Tests

(a) Comparison with Placebo Gaps from 40 Control Countries



(b) Comparison with Placebo Gaps from 30 Control Countries (discarding countries with pretreatment MSPE 10 times higher than Indonesia's)



(c) Comparison with Placebo Gaps from 11 Control Countries (discarding countries with pretreatment MSPE two times higher than Indonesia's)

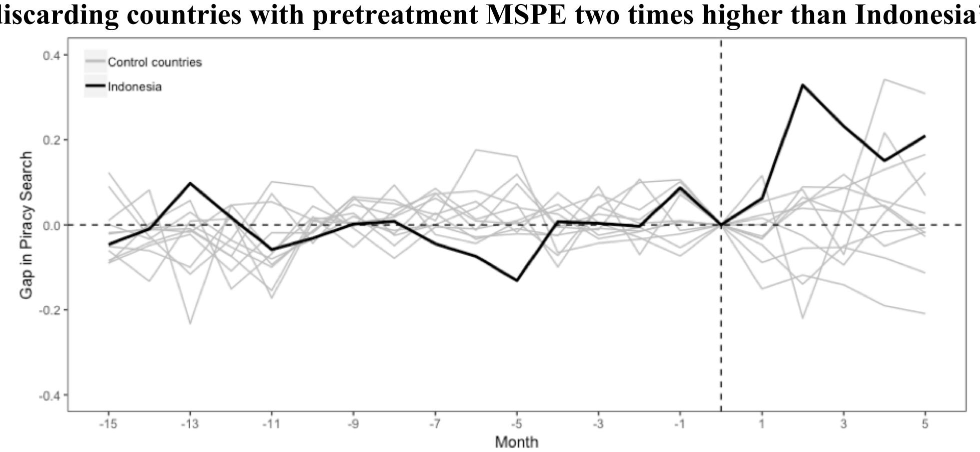
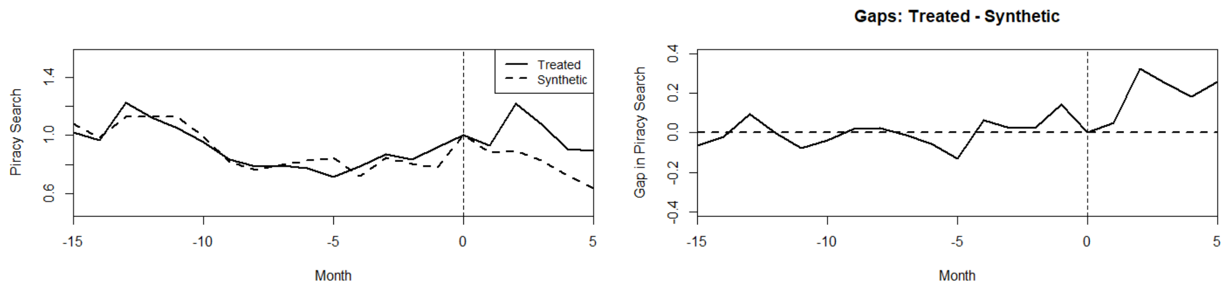
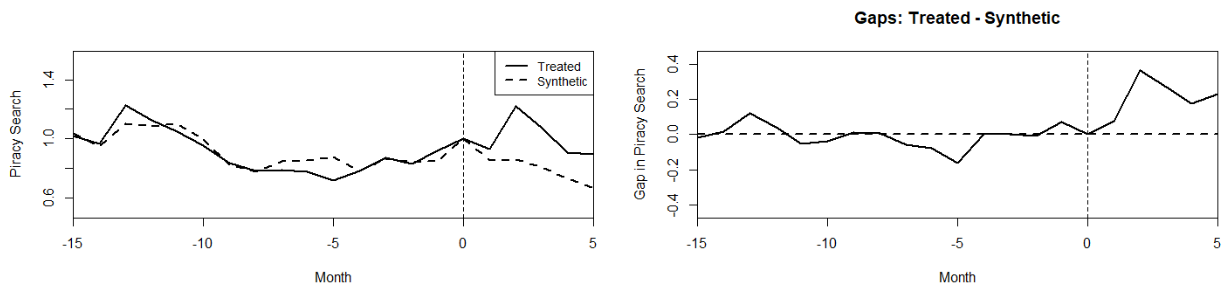


Figure 7. Trends and Gaps in Piracy Search Volume between Indonesia and Sparse Synthetic Controls

(a) Three Countries in the Control Group



(b) Two Countries in the Control Group



(c) One Country in the Control Group

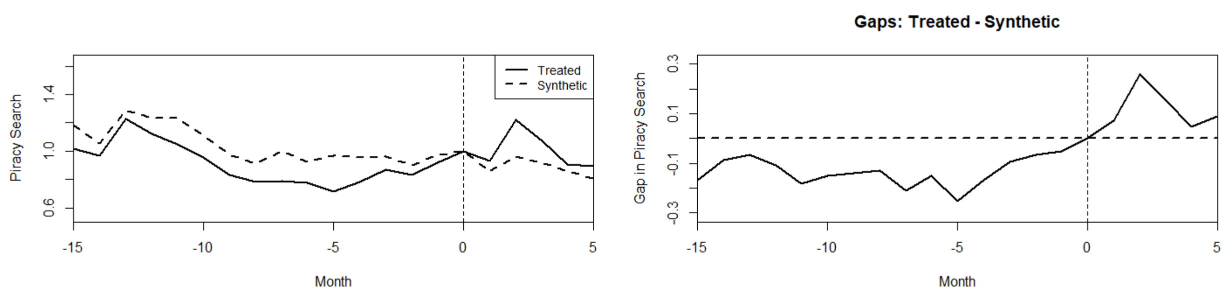


Table 1. Results from the DiD Analysis

	DV = Normalized Piracy Search Volume
Event (β)	–0.085
Event × Indonesia (γ)	0.179
Country Fixed Effects	Yes
p-value of γ	
Robust standard error	0.012
Permutation inference	0.098
Number of Observations	840
R^2	0.409

Note. The p-value from permutation inference equals 4/41=0.098.

Table 2. Country Weights in the Synthetic Indonesia

Country	Weight	Country	Weight	Country	Weight
Afghanistan	-	Laos	-	South Korea	-
Armenia	-	Macau	-	Sri Lanka	-
Azerbaijan	-	Malaysia	-	Taiwan	-
Bahrain	-	Maldives	-	Tajikistan	-
Bangladesh	-	Mongolia	-	Thailand	0.427
Bhutan	-	Myanmar	-	Timor-Leste	-
Brunei	-	Nepal	-	Turkey	-
Cambodia	-	Oman	-	Turkmenistan	-
Hong Kong	-	Pakistan	-	United Arab Emirates	-
India	0.077	Palestine	0.379	Uzbekistan	-
Iraq	-	Philippines	0.116	Vietnam	-
Kazakhstan	-	Qatar	-	Yemen	-
Kuwait	-	Saudi Arabia	-		
Kyrgyzstan	-	Singapore	-		

Table 3. Mean of Pretreatment Characteristics

	Indonesia		Average of 40 Control Countries
	Real	Synthetic	
Piracy Search Volume (y_{it})	0.910	0.921	1.036
Title Search Volume	468,524	442,119	199,861
Interest in Netflix	89,067	72,636	39,154
Interest in General Piracy	92,637	178,646	77,831
Interest in Competitors	37,726	36,717	14,138
Internet Users (2014)	43,627,401	33,726,705	15,332,347
Internet Users (2015)	50,083,428	45,198,484	19,182,586

Note. Piracy search volume in each country is normalized by the level in January 2016.

Table 4. Treatment Effect for Titles with Different Degrees of Dialogue Orientation

	Effect Size (DiD)	**Effect Size (SC)**	**Post-/Pretreatment MSPE (*p*-value)**
Median-split			
High (wpm ≥ 82.1)	0.097	0.092	4.46 (0.098)
Low (wpm < 82.1)	0.274	0.256	39.68 (0.024)
Three-way split			
High (wpm ≥ 96.7)	0.047	0.050	3.41 (0.195)
Medium (71.1 ≤ wpm < 96.7)	0.127	0.117	5.87 (0.098)
Low (wpm < 71.1)	0.341	0.321	20.04 (0.024)
Four-way split			
High (wpm ≥ 102.3)	0.077	0.042	1.63 (0.317)
Medium-high (82.1 ≤ wpm < 102.3)	0.114	0.102	3.37 (0.098)
Medium-low (64.8 ≤ wpm < 82.1)	0.157	0.156	3.62 (0.073)
Low (wpm < 64.8)	0.353	0.340	40.39 (0.024)

Table 5. Synthetic Weights from a Combination of Control Countries

Synthetic Combination	Countries and Synthetic Weights			
Four Control Countries	Thailand 0.43	Palestine 0.38	Philippines 0.12	India 0.08
Three Control Countries	Thailand 0.26	Palestine 0.49	Philippines 0.25	
Two Control Countries	Thailand 0.56	Palestine 0.44		
One Control Country	Thailand 1.00			

Table 6. Estimated Effects Using Alternative Posttreatment Period

	Before iflix Entry 02/2016-06/2016			**After iflix Entry** 07/2016-04/2017				
Last month of posttreatment period	02/2016	04/2016	06/2016	08/2016	10/2016	12/2016	02/2017	04/2017
No. of months in posttreatment period	1	3	5	7	9	11	13	15
Average posttreatment gap estimates	0.060 (0.317)	0.208 (0.024)	0.197 (0.024)	0.134 (0.073)	0.109 (0.122)	0.108 (0.122)	0.104 (0.122)	0.092 (0.146)
Average gap estimates	0.197 (0.024)			0.039 (0.537)				

Note. The proportion of 41 countries with a post-/pretreatment MSPE ratio as large as Indonesia's is reported in the parentheses. A smaller proportion means a more significant effect of treatment.

Online Appendix A. List of 304 Netflix Titles

1 Chance 2 Dance
12 Monkeys
17 Again
2001: A Space Odyssey
300
6 Years
A Clockwork Orange
A Very Murray Christmas[*]
Advantageous
After Porn Ends
Aileen Wuornos: The Selling of a Serial Killer
Aileen: Life and Death of a Serial Killer
Akame ga Kill!
American Beauty
Anatomy of a Love Seen
Angry Birds Toons
Animal Mechanicals
Anthony Jeselnik: Thoughts and Prayers[*]
Antz
Archer
Argo
Arrow
Ascension
Atari: Game Over
Aziz Ansari: Buried Alive[*]
Back in Time
Bad Night
Bates Motel
Batman Begins
Beasts of No Nation[*]
Being Elmo: A Puppeteer's Journey
Best of Enemies
Better Call Saul
Between[*]
Black Mirror
Black Sails
Bloodline[*]
Blue Mountain State
Bo on the Go!
BoJack Horseman[*]
Breaking Bad
Broadchurch
Brooklyn Nine-Nine
Bunks
Call Me Lucky
Catch Me If You Can
Charlie and the Chocolate Factory
Chasing Ice
Chef's Table[*]
Chicken Run
Chris Tucker Live[*]
Circle
Clash of the Titans
Club de Cuervos[*]
Collateral
Coming to America
Creep
DMT: The Spirit Molecule
Danger Mouse
Dark Shadows
Dawg Fight
Derek[*]
Dinosaur Train
Doctor Who
Elementary
Elf
Ever After High[*]
Expelled
Fat, Sick & Nearly Dead
Fat, Sick & Nearly Dead 2
Fed Up
Ferris Bueller's Day Off
Finders Keepers
Flushed Away
Forensic Files
Forrest Gump
Fresh Meat
Full Metal Jacket
Gangster Squad
Get Smart
Going Clear: Scientology and the Prison of
Gotham
Grace and Frankie[*]
Gravity
Grease
Green Lantern
Gunslinger Girl
Hall Pass
Halo 4: Forward Unto Dawn
Happy Feet
Happy Feet Two
Happy Tree Friends
He's Just Not That Into You
Heartland
Hemlock Grove[*]
Heropanti
Hinterland
Horrible Bosses
Hot Girls Wanted[*]
How to Get Away with Murder
How to Train Your Dragon
Hum Aapke Hain Koun

I Am Legend	Megamind	Puss in Boots
Iliza Shlesinger: Freezing Hot[*]	Miss Fisher's Murder Mysteries	Radio Rebel
Inception	Mission Blue[*]	Rake
Indiana Jones and the Kingdom of the Crystal Skull	Mission: Impossible - Ghost Protocol	Rango
Iris	Mission: Impossible II	Ray Donovan
Jane the Virgin	Mission: Impossible III	Real Rob
Jen Kirkman: I'm Gonna Die Alone (And I Feel Fine)[*]	Mitt[*]	Residue
Joe Rogan: Live	Monsters vs Aliens	Results
John Mulaney: The Comeback Kid[*]	My Babysitter's a Vampire	Rhymes for Young Ghouls
Joseph: King of Dreams	My Little Pony: Equestria Girls	Richie Rich[*]
Journey 2: The Mysterious Island	My Little Pony: Friendship Is Magic	River[*]
Journey to Le Mans	MythBusters	Rubble Kings
Keith Richards: Under the Influence[*]	Naomi and Ely's No Kiss List	Rurouni Kenshin
Kevin Hart: Let Me Explain	Narcos[*]	Rush Hour 3
Kung Fu Panda 2	New Year's Eve	Russell Brand: End the Drugs War
Kurt & Courtney	No Reservations	Russell Peters: Notorious[*]
Last Days in Vietnam	No Strings Attached	Saving Private Ryan
Life's Too Short	Ocean's Eleven	Scooby-Doo
Lilyhammer[*]	Ocean's Thirteen	Scream[*]
Line of Duty	Ocean's Twelve	Sense8[*]
Little Witch Academia	Oggy and the Cockroaches	Sex and the City 2
Living on One Dollar	Orange Is the New Black[*]	Shadowhunters[*]
Luther	Over the Hedge	Shahid
Madagascar	Pacific Rim	Shark Tale
Madagascar 3: Europe's Most Wanted	Peaky Blinders	Sharknado
Maine Pyar Kiya	Pee-wee's Playhouse	Sharknado 2: The Second One
Making a Murderer[*]	Peg + Cat	Sherlock Holmes
Man of Steel	Penny Dreadful	Sherlock Holmes: A Game of Shadows
Man on Fire	Peppa Pig	Shrek
Manson Family Vacation	Piku	Shrek 2
Marco Polo[*]	Pirate's Passage	Shrek Forever After
Marco Polo: One Hundred Eyes[*]	Pretty Little Liars	Shrek the Halls
Marvel's Daredevil[*]	Project X	Shutter Island
Marvel's Jessica Jones[*]	Puffin Rock[*]	Sid the Science Kid
Master of None[*]	Pumping Iron	Sinbad: Legend of the Seven Seas

Skins	The Hunting Ground	Top Boy
Some Assembly Required*	The IT Crowd	Top Gun
Somm	The Inbetweeners	Trailer Park Boys*
Soul Eater	The Last Song	Trailer Park Boys: Say Goodnight to the Bad Guys
Space Racers	The Lord of the Rings: The Fellowship of the Ring	Transformers Prime
Spartacus	The Lord of the Rings: The Return of the King	Transformers: Dark of the Moon
Special Ops Mission	The Lord of the Rings: The Two Towers	Transformers: Rescue Bots
Spirit: Stallion of the Cimarron	The Lucky One	Transformers: Revenge of the Fallen
Star Trek	The Magic School Bus	Twinsters
Staten Island Summer	The Matrix	Two Weeks Notice
Strawberry Shortcake	The Matrix Reloaded	Unbreakable Kimmy Schmidt*
Suits	The Matrix Revolutions	Under the Dome
Super High Me	The Mind of a Chef	Utopia
Superman Returns	The Nightmare	Vexed
Swearnet: The Movie	The Notebook	Video Game High School
That '70s Show	The One I Love	Virunga*
The 100	The Originals	W/ Bob & David*
The Battered Bastards of Baseball*	The Polar Express	Wakfu
The Blacklist	The Prince of Egypt	We're the Millers
The Bletchley Circle	The Propaganda Game	Weeds
The Chosen	The Returned*	Wentworth
The Covenant	The Ridiculous 6*	Wet Hot American Summer
The Dark Knight Rises	The Road to El Dorado	What Happened Miss Simone?*
The Delivery Man	The Search for General Tso	Wild Kratts
The Dictator	The Shining	Winter on Fire: Ukraine's Fight for Freedom*
The Driver	The Short Game*	Winx Club
The Fall	The SpongeBob SquarePants Movie	Wrath of the Titans
The Fluffy Movie	The Terminal	Yes Man
The Godfather	The Town	Zapped
The Great Gatsby	The True Cost	Zeitgeist: Addendum
The Hangover	Tig*	Zeitgeist: Moving Forward
The Hangover: Part II	Timmy Time	
The Hangover: Part III	To Kill a Mockingbird	

* Netflix originals.

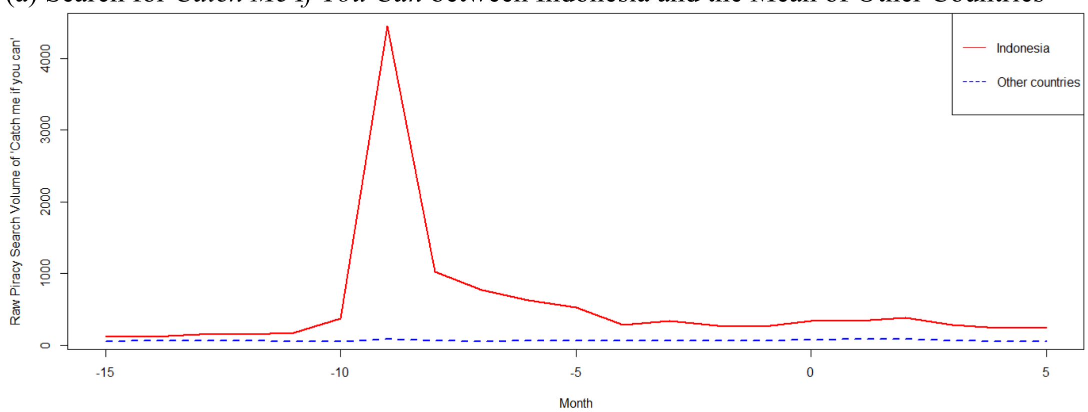
Online Appendix B. Robustness Check of Synthetic Control Method Using 304 Titles

Two titles, *Catch Me If You Can* and *Piku*, were dropped from the main analysis because of serious anomalies in search data, as shown in Figure B.1. Notably, in April 2015 ($t = -9$ in Figure B.1), a South Korean pop band named Girls' Generation (also known as SNSD) released a massively successful song called "Catch Me If You Can" (Benjamin 2015), which contaminated the search volume for the movie with the same name in most East Asian and Southeast Asian countries. We also find substantially different piracy demand for *Piku* in only one country (India), which is where it was produced.

In this appendix, we report the results from the synthetic control method using data of 304 titles, which includes *Catch Me If You Can* and *Piku*. Table B.1 and Table B.2 report the weight allocation across control countries and the pretreatment fit. We also create the trend and gap plots of piracy search volume between the actual Indonesia and the synthetic Indonesia in Figure B.2. The mismatch in piracy search volume from $t = -10$ to $t = -5$ is likely due to abnormal search volume in *Catch Me If You Can* and *Piku* during this period. The average posttreatment gap estimate using 304 titles is 0.196, which is similar to what we found in the main analysis, suggesting the robustness of our findings with respect to the drop of outliers. The post-/pretreatment MSPE ratio for Indonesia is 8.26, which ranks 1 out of 41, suggesting a p-value of 0.024.

Figure B.1. Piracy Search Volume of *Catch Me If You Can* and *Piku*

(a) Search for *Catch Me If You Can* between Indonesia and the Mean of Other Countries



(b) Search for *Piku* between India and the Mean of Other Countries

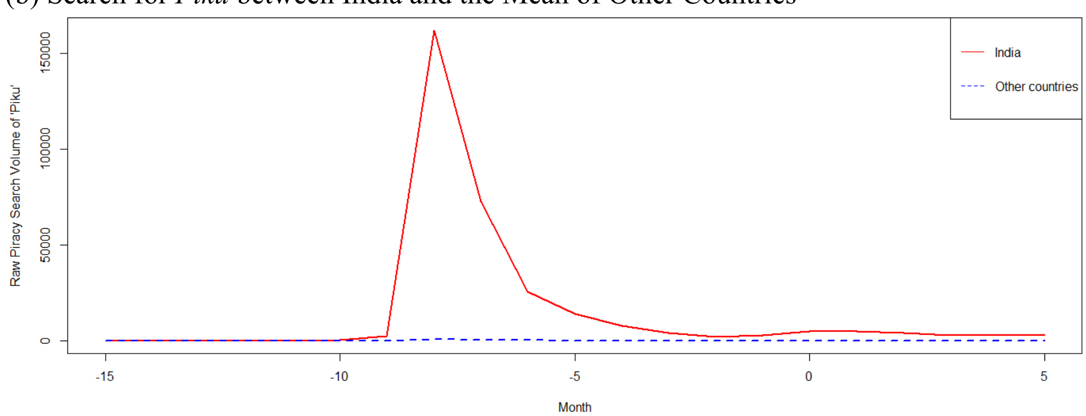


Figure B.2. Trends and Gaps in Piracy Search Using 304 Titles: Indonesia vs. Synthetic Control

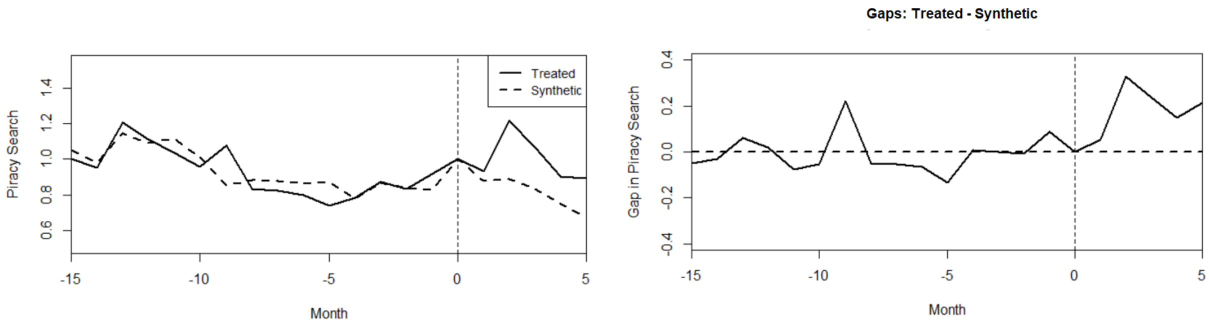


Table B.1. Country Weights in the Synthetic Indonesia Using 304 Titles

Country	Weight	Country	Weight	Country	Weight
Afghanistan	-	Laos	-	South Korea	-
Armenia	-	Macau	-	Sri Lanka	-
Azerbaijan	-	Malaysia	0.236	Taiwan	-
Bahrain	-	Maldives	-	Tajikistan	-
Bangladesh	-	Mongolia	-	Thailand	0.244
Bhutan	-	Myanmar	-	Timor-Leste	-
Brunei	-	Nepal	-	Turkey	-
Cambodia	-	Oman	-	Turkmenistan	-
Hong Kong	-	Pakistan	-	United Arab Emirates	-
India	0.038	Palestine	0.381	Uzbekistan	-
Iraq	-	Philippines	0.101	Vietnam	-
Kazakhstan	-	Qatar	-	Yemen	-
Kuwait	-	Saudi Arabia	-		
Kyrgyzstan	-	Singapore	-		

Table B.2. Mean of Pretreatment Characteristics Using 304 Titles

	Indonesia		Average of 40 Control Countries
	Real	Synthetic	
Piracy Search Volume	0.930	0.938	1.054
Title Search Volume	474,110	373,181	206,196
Interest in Netflix	89,067	64,589	39,154
Interest in General Piracy	92,637	111,212	77,831
Interest in Competitors	37,726	37,057	14,138
Internet Users (2014)	43,627,401	24,325,676	15,332,347
Internet Users (2015)	50,083,428	30,395,634	19,182,586

Online Appendix C. Additional DiD Specifications and Model-Free Evidence

C.1. Alternative presentations and specifications of the DiD Model

We report several two-by-two, diff-in-diff style tables as alternative presentations of the data. We report the level of piracy search volume in raw, normalized, and logged values in Tables C.1-C.3, where highlighted cells present the DiD estimates. All three tables indicate that there is an increase in piracy search volume in Indonesia after the treatment, relative to the other 40 countries where Netflix entered and remained available, suggesting the robustness of our findings to alternative specifications of the DiD model.

C.2. Additional model-free evidence from individual control markets

We present additional model-free evidence for the treatment effect. Specifically, we

1) compare the fit between Indonesia and each control market,
2) plot trend comparisons between Indonesia and each of the 40 control countries to visualize the treatment effect,
3) estimate the size of the treatment effect between Indonesia and each control market.

To make this analysis meaningful across countries of different sizes, we focus on the normalized piracy search volume so that they are on the same scale. This allows us to compare the quality of fit between each country and Indonesia to quantitatively see which countries have the most similar time series.

C.2.1. *Pretretment fit by countries.* We report the pretreatment MSPE across 40 control countries in Figure C.1. We also include the pretreatment MSPE for the synthetic Indonesia (42.7% of Thailand + 37.9% of Palestine + 11.6% of Philippines + 7.7% of India; *Indonesia_SC* on the Y-axis) and the control that assigns equal weight to 40 countries (*Indonesia_DiD* on the Y-axis). The pretreatment MSPE of a control country i is calculated as $MSPE_i = \frac{1}{15}\sum_{t=-15}^{-1}\left(\bar{y}_{it} - \bar{y}_{jt}\right)^2$, where $\bar{y}_{it}$ and $\bar{y}_{jt}$ are the mean-centered monthly normalized piracy search for the control and the treated country respectively. A smaller MSPE indicates a better pretreatment fit.

Two observations are noteworthy. First, the synthetic control method leads to a control country that fits Indonesia 27.5% better than the control with equal weights used in the DiD (1-0.0037/0.0051=0.275). Second, using an individual country as the control fits Indonesia strictly worse (greater pretreatment MSPE) than the synthetic Indonesia except for one country, Thailand. The reason the synthetic Indonesia has a larger MSPE than Thailand is because we included several other matching characteristics in the synthetic control matching, as recommended by the literature (Abadie et al. 2010, 2015). Nevertheless, the largest weight on Thailand in the synthetic Indonesia provides some external validity to the synthetic control method.

We classify the 40 control countries into 4 groups based on their pretreatment fit with Indonesia:

1. 3 countries (Thailand, Malaysia, Brunei) whose pretreatment MSPE ≤ 0.005 are classified to the "best fitting" control group;
2. 7 countries (United Arab Emirates, Oman, Palestine, Maldives, Taiwan, Kazakhstan, Hong Kong) remain in the top quartile of fit;
3. 10 countries (Cambodia, Pakistan, Saudi Arabia, Azerbaijan, Bahrain, Sri Lanka, Kuwait, Qatar, Bangladesh, Nepal) fall into the second quartile;
4. 20 countries (Iraq, India, Armenia, Myanmar, South Korea, Uzbekistan, Turkey, Philippines, Mongolia, Vietnam, Yemen, Singapore, Macau, Afghanistan, Laos, Tajikistan, Kyrgyzstan, Bhutan, Turkmenistan, Timor-Leste) fall into the bottom half of fit. These countries generally have a very poor fit with Indonesia.

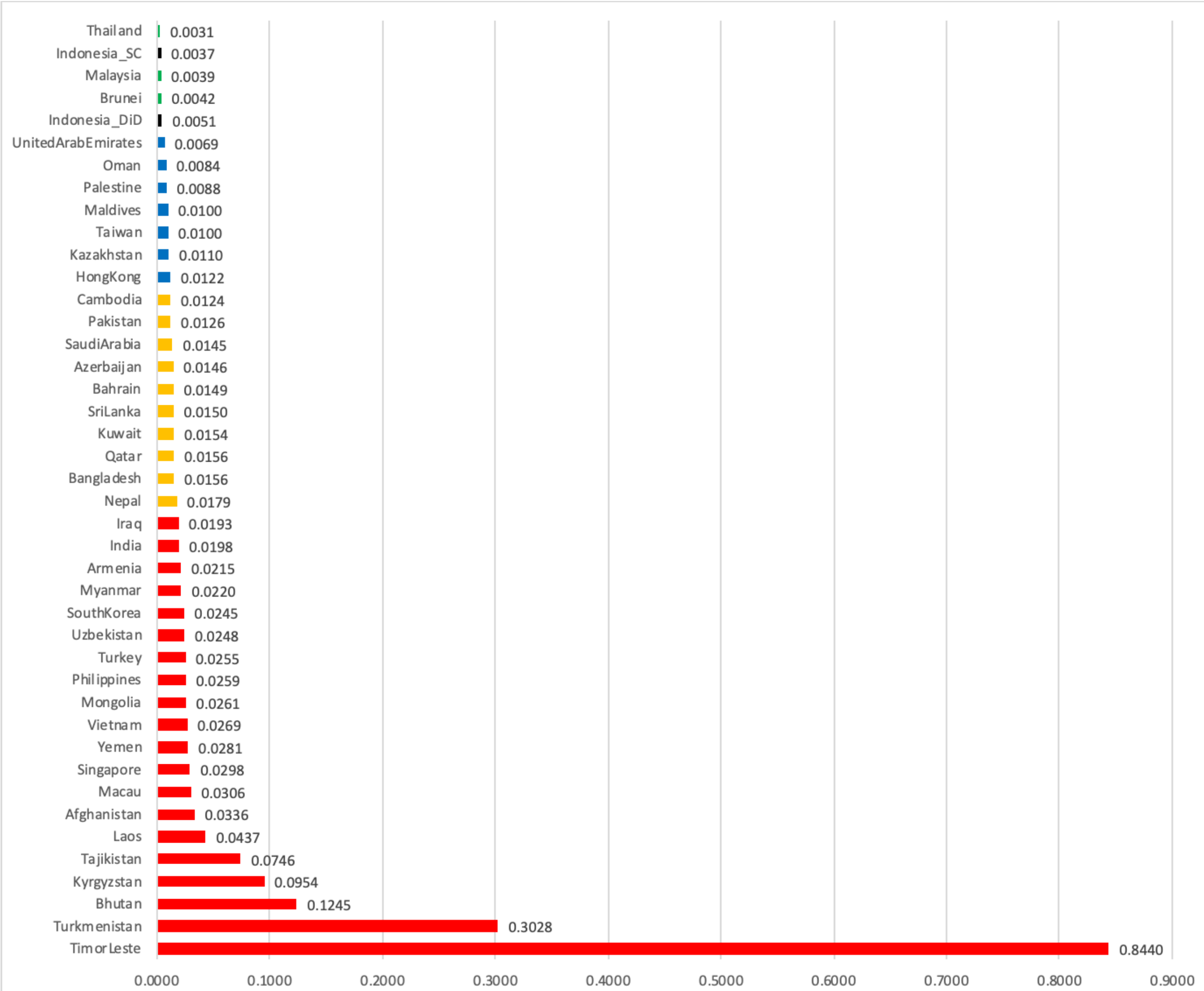
C.2.2. *Trend comparisons*. We present the trend comparison between Indonesia and the three best fitting control countries in Figure C.2. To better visualize whether the parallel trend is likely to exist, we mean shift the normalized piracy search of the control country so that the first month's ($t = -15$) gap between the control and Indonesia is zero.

The parallel trend assumption seems to hold well in Thailand, Malaysia, and Brunei because of the relatively small pretreatment gaps. For these three countries, we observe a clearly positive posttreatment gap, which provides model-free evidence for the positive treatment effect of Netflix's unavailability in Indonesia.

For the remaining control countries in the top quartile, we observe a generally positive posttreatment gap only in some countries (United Arab Emirates, Palestine, Taiwan, Hong Kong). However, the parallel trend assumption is unlikely to hold in any of these countries after inspecting the pretreatment trends between Indonesia and the control country. Our observations of the parallel trend in countries outside of the top quartile show a generally poor fit. This suggests that a synthetic control model may do a better job of matching pieces of regions.

C.2.3. *DiD estimates by countries.* We further investigate the treatment effect when using each of the 40 countries as the control. Several findings emerge from the DiD estimates reported in Table C.4. First, the majority of DiD estimates are positive and none of negative estimates are statistically significant. This suggests that the change in piracy search in Indonesia after the treatment is greater than in most control countries. Second, despite the small sample size (40 observations in each DiD regression), more than half (21 of 40) of the DiD estimates are positive and statistically significant at 0.10, and 45% (18 of 40) are statistically significant at 0.05; and all DiD estimates are significant at 0.10 if we focus on the best fitting control countries. Third, among the 21 statistically significant DiD estimates ($p < 0.10$), the effect size is always greater than the 19.7% increase found from the synthetic control method, with the exception of the 19.6% effect size from using Palestine as the control. This observation implies that the treatment effect from synthetic control method may be conservative. In sum, the DiD estimates using each individual country as the control provides additional evidence for the positive treatment effect.

Figure C.1. Pretreatment MSPE across Countries



Notes. **Black**: synthetic Indonesia and the control used in the DiD model; **Green**: best fitting control countries with pretreatment MSPE $\leqslant$ 0.005; **Blue**: remaining control countries in the top quartile of fit; **Yellow**: countries in the second quartile of fit.; **Red**: countries in the bottom half of fit.

Figure C.2. Trend Comparisons for the Three Best Fitting Control Countries

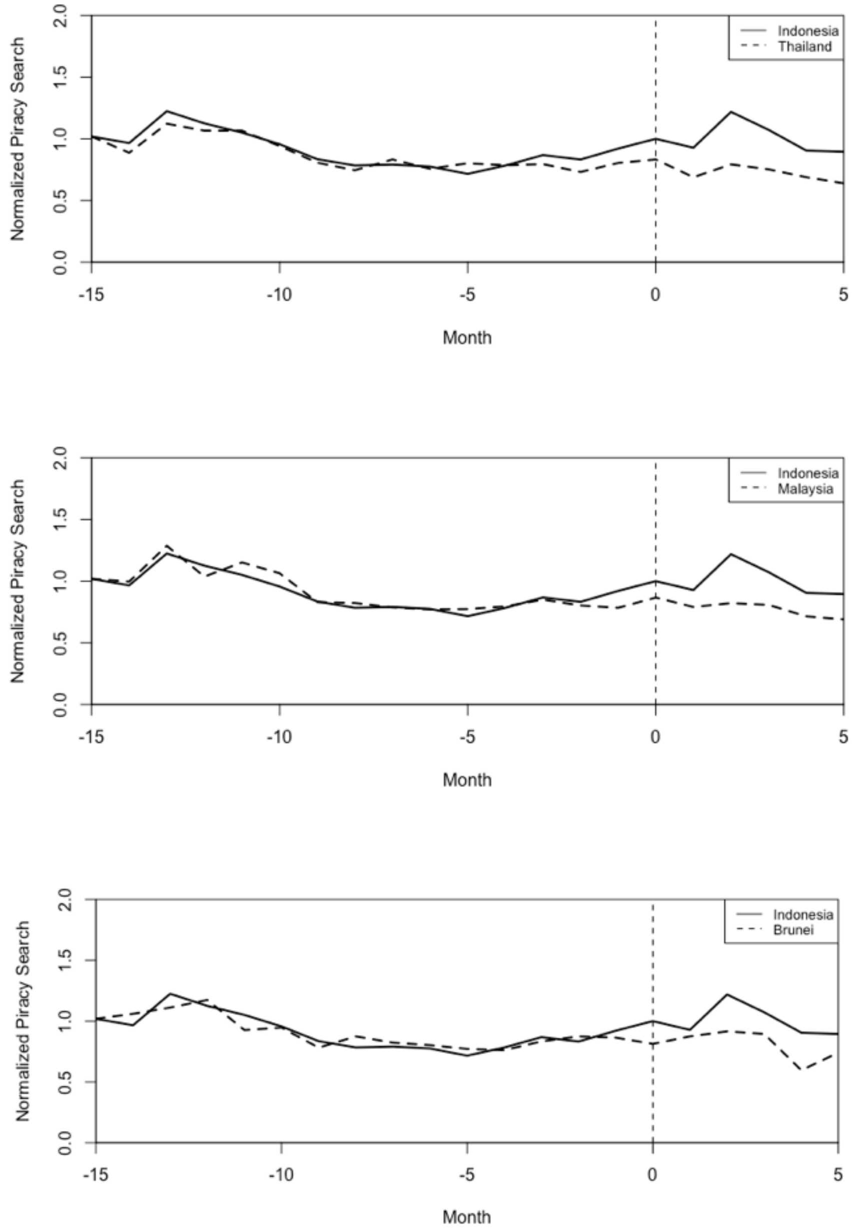


Table C.1. Raw Piracy Search Volume between Indonesia and Control Countries before and after the treatment

Raw piracy search volume	Pretreatment ($-15 \leq t \leq -1$)	Treatment ($t = 0$)	Posttreatment ($1 \leq t \leq 5$)	Difference (post–pre)
Indonesia (treated)	15393 (2469)	16920 (·)	16984 (2368)	1591
40 Asian countries (control)	4634 (9841)	4875 (11728)	4426 (10427)	–207
Difference (treated–control)	10759	-	12558	**1799**

Notes. Standard deviation in parentheses.

Table C.2. Normalized Piracy Search Volume between Indonesia and Control Countries before and after the treatment

Normalized piracy search volume	Pretreatment ($-15 \leq t \leq -1$)	Treatment ($t = 0$)	Posttreatment ($1 \leq t \leq 5$)	Difference (post–pre)
Indonesia (treated)	0.910 (0.146)	1.000 (·)	1.004 (0.140)	0.094
40 Asian countries (control)	1.036 (0.315)	1.000 (0)	0.951 (0.263)	–0.085
Difference (treated–control)	–0.126	-	0.053	**0.179**

Notes. Standard deviation in parentheses.

Table C.3. Log of Piracy Search Volume between Indonesia and Control Countries before and after the treatment

Log of piracy search volume	Pretreatment ($-15 \leq t \leq -1$)	Treatment ($t = 0$)	Posttreatment ($1 \leq t \leq 5$)	Difference (post–pre)
Indonesia (treated)	9.630 (0.155)	9.736 (·)	9.733 (0.134)	0.103
40 Asian countries (control)	7.176 (1.695)	7.182 (1.726)	7.086 (1.738)	–0.090
Difference (treated–control)	2.454	-	2.647	**0.193**

Notes. Standard deviation in parentheses.

Table C.4. DiD Estimates Using an Individual Country as the Control

Group	Control country	Pretreatment MSPE	DiD Estimates
Best fitting countries (3 countries)	Thailand	0.0031	0.259 (0.097) **
	Malaysia	0.0039	0.247 (0.106) **
	Brunei	0.0042	0.198 (0.101) *
Rest of top quartile of control countries (7 countries)	United Arab Emirates	0.0069	0.218 (0.088) **
	Oman	0.0084	0.059 (0.083)
	Palestine	0.0088	0.196 (0.096) **
	Maldives	0.0100	0.110 (0.101)
	Taiwan	0.0100	0.225 (0.088) **
	Kazakhstan	0.0110	0.216 (0.094) **
	Hong Kong	0.0122	0.200 (0.086) **
Second quartile of control countries (10 countries)	Cambodia	0.0124	0.137 (0.087)
	Pakistan	0.0126	0.264 (0.090) ***
	Saudi Arabia	0.0145	0.213 (0.100) **
	Azerbaijan	0.0146	0.216 (0.106) **
	Bahrain	0.0149	0.140 (0.093)
	Sri Lanka	0.0150	0.015 (0.088)
	Kuwait	0.0154	0.140 (0.087)
	Qatar	0.0156	0.216 (0.095) **
	Bangladesh	0.0156	-0.101 (0.085)
	Nepal	0.0179	-0.074 (0.086)
Bottom half of control countries (20 countries)	Iraq	0.0193	0.029 (0.083)
	India	0.0198	0.007 (0.080)
	Armenia	0.0215	0.280 (0.101) ***
	Myanmar	0.0220	-0.105 (0.101)
	South Korea	0.0245	0.270 (0.142) *
	Uzbekistan	0.0248	-0.074 (0.133)
	Turkey	0.0255	0.333 (0.114) ***
	Philippines	0.0259	0.195 (0.152)
	Mongolia	0.0261	0.473 (0.153) ***
	Vietnam	0.0269	0.263 (0.121) **
	Yemen	0.0281	-0.160 (0.135)
	Singapore	0.0298	0.381 (0.158) **
	Macau	0.0306	0.281 (0.133) **
	Afghanistan	0.0336	0.279 (0.142) *
	Laos	0.0437	0.205 (0.143)
	Tajikistan	0.0746	0.419 (0.165) **
	Kyrgyzstan	0.0954	0.220 (0.174)
	Bhutan	0.1245	0.201 (0.197)
	Turkmenistan	0.3028	0.461 (0.325)
	Timor-Leste	0.8440	0.094 (0.451)

Notes. Standard errors in parentheses. $N = 40$ in each DiD regression.
*$p < 0.1$, **$p < 0.05$, ***$p < 0.01$.

Online Appendix D. Additional Investigations of Model Assumptions and Results

D.1. Further investigation of potential cross-country spillover effects
Cross-country effects may occur if people in Indonesia read news from foreign countries and spread WOM to affect piracy search behavior of others. We provide two pieces of empirical evidence which suggest that this was unlikely or not substantial.

First, we identify popular websites where Indonesians obtain information about TV shows and movies. To do so, we used SimilarWeb and the Wayback Machine to identify the top 50 most visited websites in Indonesia in July 2017, the earliest record available.[16] We find that the top 50 websites in the media, news, and entertainment categories are all local Indonesian websites (detik.com, kompas.com, uzone.id, tribunnews.com, liputan6.com, kapanlagi.com) with the exception of YouTube, an international website. Therefore, we fail to find evidence that Indonesians predominantly visit entertainment websites from other Asian countries.

Second, we examine the popularity of mainstream newspaper and TV channels in the four control countries that constitute the synthetic Indonesia during the posttreatment period. We compare the search volume of the most read (viewed) newspaper (TV channels) in each of the four control countries with that of the most read (viewed) newspaper (TV channels) in Indonesia using Google Trends. For newspapers, the most circulated newspaper in Indonesia and the four control countries are Kompas (Indonesia), Dainik Bhaskar (India), Philippines Daily Inquirer (the Philippines), VnExpress (Thailand), and Al-Quds (Palestine). For TV channels, the most prominent local TV channels are ANTV (Indonesia), Sun TV (India), ABS-CBN (the Philippines), 7 HD (Thailand), and Al-Aqsa TV (Palestine). We report the head-to-head comparison of search volumes on Google in Figure D.1 and Figure D.2. The flat curves of search volume of the mainstream news media and TV channels from the four control countries indicate that these foreign media sources were rarely searched for by Indonesians during the posttreatment period, which again does not support the existence of spillovers of WOM across countries.

D.2. Consideration of cross-country price variation
If Netflix charged a higher price in certain countries than others, the substitution between piracy and paid content would be different across countries, and therefore renders the Netflix' service to be incomparable. To investigate the extent of price variation, we collected data on prices for the basic subscription offered by Netflix in each of the four synthetic control countries (India[17], Palestine[18], the Philippines[19], Thailand[20]) during the posttreatment window. We find that the basic subscription of Netflix across these countries costs between $7 and $8 a month using the currency rates in January 2016, suggesting a relatively small price variation across countries.

We also find a webpage listing Netflix prices in July 2017 around the world (Baker 2017). The most common price for the basic Netflix subscription was $7.99 USD, especially among Asian countries. This observation provides further evidence for the small price variation across countries in this study. We also did not find any evidence for price changes in India, Palestine, the Philippines, and Thailand during the posttreatment period.

[16] https://web.archive.org/web/20170713085424/https://www.similarweb.com/top-websites/indonesia
[17] https://gadgets.ndtv.com/tv/news/netflix-launched-in-india-plans-start-at-rs-500-per-month-786529
[18] https://bit.ly/3ael0v1. We searched for "Netflix price Palestine" in Google and sets the date range from January 1 to January 31, 2016. The snippet from Netflix's web page in Palestine suggests that the price of basic Netflix subscription in Palestine was 7.99 USD in January 2016.
[19] https://cnnphilippines.com/entertainment/2016/01/07/Netflix-Philippines-prices-Netflix-Everywhere-TV-series-movies-streaming.html
[20] https://www.bangkokpost.com/learning/work/818956/netflix-expands-to-thailand

D.3. Discussion of the exclusion of similar countries in the synthetic control group
One possible explanation for the exclusion of similar countries in the control group, such as Malaysia, is that the similarities between Indonesia and Malaysia has already been adequately captured by the relationship between Indonesia and other four countries that constitute the synthetic control group. This is a common occurrence in synthetic control models (e.g., Abadie et al. 2010), and we provide evidence that it is the case here as well by first comparing piracy search in Malaysia to other control countries and then by investigating an alternative synthetic control specification.

Comparing Malaysia to other control countries. Interestingly, the piracy search dynamics in Malaysia is a strong match to the weighted combination of the Philippines and Thailand, which are both members of our synthetic control model. In particular, in Figure D.3 we show the period-by-period comparison between Malaysia and a weighted combination of the Philippines and Thailand. We set the weight to be consistent with the relative importance of the Philippines (11.6%) and Thailand (42.7%) in the synthetic Indonesia (11.6/(42.7+11.6) = 21.4% for the Philippines and 42.7/(42.7+11.6) = 78.6% for Thailand).

As Figure D.3 shows, the temporal variation in piracy search in Malaysia is well captured by the weighted combination of the Philippines and Thailand, both before and after the treatment. This implies that the fit between the synthetic and actual Indonesia will not be substantially improved by the inclusion of Malaysia, conditional on the inclusion of the Philippines and Thailand. This provides support for the absence of Malaysia in the synthetic control group.

Alternative synthetic control model excluding Thailand and the Philippines. An alternative way to approach this question is to remove the overlapping control countries (Thailand and the Philippines) and re-estimate the synthetic control model. If there is indeed a substantial overlap, then Malaysia should have a large weight in the new model. This is precisely what we find.

Excluding both the Philippines and Thailand from the synthetic control model leads to a result where the new synthetic Indonesia places the largest weight on Malaysia (47%), followed by Palestine (45%) and India (3%). This model also places small non-zero weights (between 0.1% and 0.3%) on a subset of other countries. Figure D.4 shows the trend and gap plots of piracy search volume between the actual Indonesia and the synthetic Indonesia. These two plots are similar to the trend and gap plots (Figures 3 and 4 in the article) when the Philippines and Thailand were included in the potential control. The gap estimate of the treatment effect is 0.212, which is also close to the effect size of 0.197 in our main analysis.

A second possible explanation for the exclusion of a country such as Malaysia from the synthetic control group is that although this country shares similarities with Indonesia in many aspects, they are less similar with respect to piracy behavior. Malaysia has a much higher piracy rate (defined as the percentage of population who visited piracy sites) than Indonesia. According to MUSO, Malaysia has a piracy rate almost twice as much as that of Indonesia. We provide further support to this discrepancy between Indonesia and Malaysia using our data on pretreatment piracy search volumes. We create a piracy ranking in 2015 based on average monthly piracy search volume per capita for the Netflix titles in our study. We find that Malaysia is ranked 11th, showing considerably higher piracy search per capita than Indonesia, which is ranked 26th. Thailand is ranked 18th and the Philippines is ranked 28th, showing that the two Southeast Asian countries in the synthetic control group are indeed more similar to Indonesia with respect to online piracy search. It is also worth noting that the correlation between our own piracy ranking and the MUSO's is 0.85 across the 13 Asian countries that are available in MUSO's report, which provides some external validity of this investigation.

D.4. Further discussion of Netflix's short availability in Indonesia

It is theoretically possible that the short availability of Netflix in Indonesia might drive consumers to increase search for piracy in subsequent months because of the generated demand for content. If such a carryover effect of the short operation of Netflix really exists, we expect to see an immediate increase in piracy search in Indonesia after January 2016. However, we actually observe a dip rather than a bump in February 2016 (see Figure 3 at t = 1), which is inconsistent with what the carryover effect predicts. The presence of this carryover effect predicts that the unavailability of Netflix in Indonesia should lead to more piracy search for TV shows rather than movies because TV shows typically include more content (because of multiple episodes and multiple seasons) and therefore are more likely to be consumed over a longer time span. This prediction is again not supported by the data. As Table D.1 shows, the piracy search volume for TV shows actually decreased in February and March 2016, compared to that in January. The data therefore fails to support a potential carryover effect of Netflix's three-week availability in Indonesia, suggesting that the estimate of the treatment effect (Netflix's failure to launch) is unlikely biased by the short operation of Netflix in Indonesia.

D.5. Discussion of posttreatment variations in piracy search in Indonesia

We investigate the spikes in piracy search in Indonesia in March and April 2016. First, we check whether the spikes in these two months are abnormal. The first row in Table D.1 reports the normalized piracy search in Indonesia from January to June 2016. Although the piracy search volume in March and April is 21.9% and 7.3% higher than that of January, we saw a decline in piracy search volume in February (-7.8%), May (-9.6%), and June (-10.5%). In fact, the mean of normalized piracy search in the 5 posttreatment months is 1.004. Thus, the piracy search on average remained the same in Indonesia after the treatment – which is consistent with the null effect in Indonesia due to Netflix's unavailability. As the two spikes in March and April did not lead to a significant increase in piracy search in Indonesia after the treatment, these two spikes do not appear to be outliers.

We also examine whether the 21.9% mean deviation in March 2016 was unprecedented. To check this, we calculate the mean deviation for each month before the treatment by the difference in normalized piracy search and the mean level during the 15 pretreatment months. The range of the mean deviations during the pretreatment period is from -19.4% to 31.5%. In addition, the mean deviations in both December 2014 (31.5%) and January 2015 (21.6%) are either larger or similar to that in March 2016. We therefore conclude that the spike in March 2016 was not unprecedented and should not be excluded from the estimation of the treatment effect.

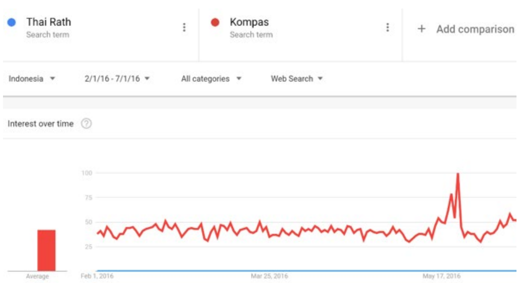
To better understand the potential drivers of the spike, we break down the piracy search volume to that from TV shows and movies (row 2 and row 3 in Table D.1.). We find that the positive demand shock in March 2016 was mainly driven by the demand for movies rather than TV shows. Although we do not have a definitive explanation for why this happened in March 2016, we can speculate that this unobserved positive demand shock for movies was related to the Oscar ceremony, which took place at the end of February (Feb 28^{th}, 2016) and might drive the overall interest in movie consumption in March.

Figure D.1. Comparing Search Volume of Foreign and Local Newspapers in Indonesia

India vs. Indonesia

Philippines vs. Indonesia

Thailand vs. Indonesia



Palestine vs. Indonesia

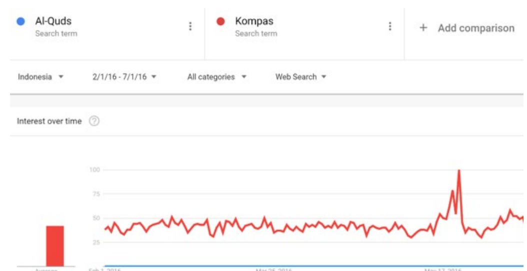
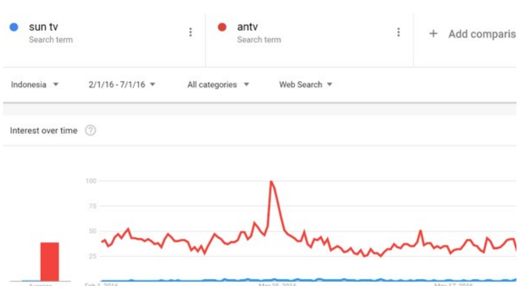
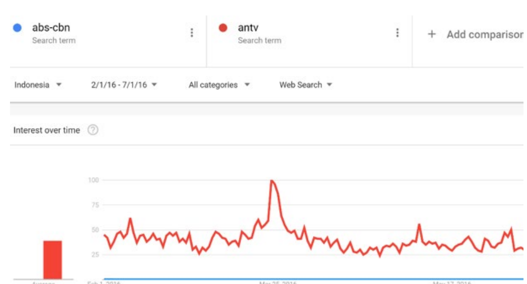


Figure D.2. Comparing Search Volume of Foreign and Local TV Channels in Indonesia

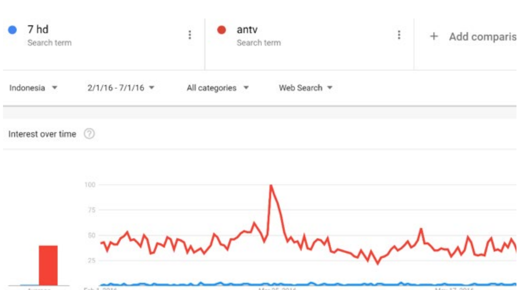
India vs. Indonesia



Philippines vs. Indonesia



Thailand vs. Indonesia



Palestine vs. Indonesia

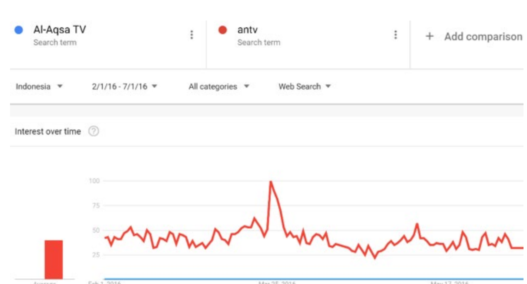


Figure D.3. Trend Comparisons between Malaysia and the Weighted Combination of the Philippines and Thailand

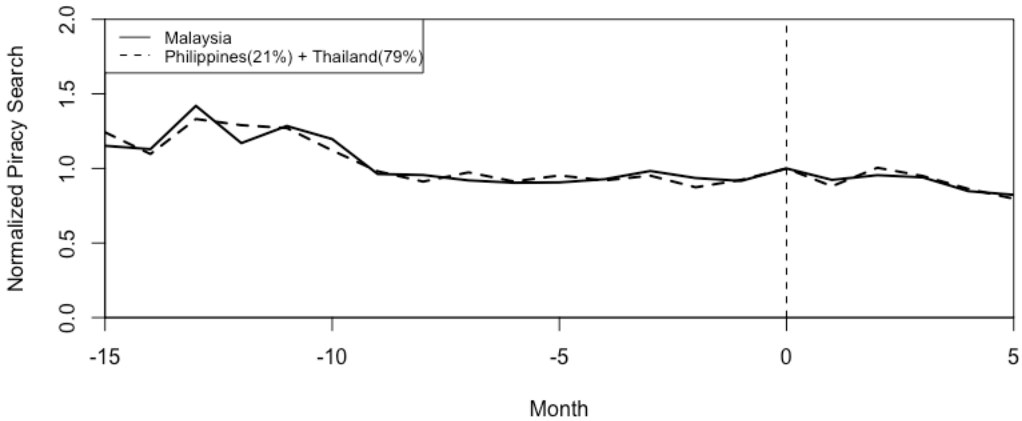


Figure D.4. Trends and Gaps in Piracy Search When Excluding the Philippines and Thailand

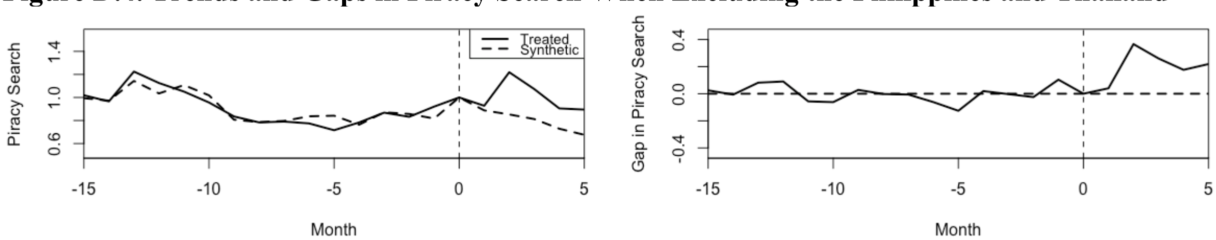


Table D.1. Piracy Search Volume in Indonesia after the Treatment

	Jan 2016	Feb 2016	Mar 2016	Apr 2016	May 2016	Jun 2016
Normalized piracy search	1.000	0.928	1.219	1.073	0.904	0.895
Piracy search volume (TV shows)	4,350	3,960	3,810	4,120	4,030	4,160
Piracy search volume (movies)	12,570	11,740	16,810	14,030	11,280	10,980
Piracy search volume (total)	16,920	15,700	20,620	18,150	15,310	15,410

Online Appendix E. Supplementary Investigations Related to the Substitution and Market Expansion Effects

We first provide empirical support for the theorized stronger substitution effect for original than nonoriginal titles. We then rule out an alternative explanation for the smaller effect for original titles due to the lack of piracy availability. Last, we provide additional evidence for the market expansion effect.

E.1. Assumptions for the stronger substitution effect for original titles

Our argument for the stronger substitution effect for original over nonoriginal titles relies on two implicit assumptions. First, unlike original titles that are exclusively available on Netflix, nonoriginal titles are available on other legal channels. Second, both original and nonoriginal titles are available on piracy sites. Under these two assumptions, we expect a greater substitution effect for original than nonoriginal titles because consumers are only able to consume pirated content for original titles, while they can choose between other legal channels and piracy sites for nonoriginal titles, when Netflix is unavailable.

We empirically verify the first assumption by showing that there were at least two leading DVD rental service providers in Indonesia at the time of this study (2015–2016). Video Ezy, Goal Disc, and DVD Club were the three largest DVD rental service providers in Indonesia in 2011 (Fahriyadi 2011). We find that in 2018, there were 65 Video Ezy stores in Indonesia and Goal Disc was still offering franchise opportunities (Shetty 2018, ThaiFranchiseCenter 2018). It is therefore reasonable to assume that Indonesians were able to consume nonoriginal content through legal channels between 2011 and 2018, which covered period of analysis.

For the second assumption, we manually checked whether there were torrents uploaded before January 27, 2016, to the three popular torrent sites for each of the 302 titles used in the main analysis. Specifically, we focused on the availability of torrents on The Pirate Bay, RARBG, and 1337x, which were popular torrent sites in 2016 that were still live as of November 2019, when we collected data on piracy availability (Ernesto 2016b, 2018). As we inferred piracy availability from archived data from three torrent sites, our measure of piracy availability is conservative, because a pirated copy could have been uploaded to one of these three sites before 2016 and later removed or a pirated copy could have been available on other torrent sites. A search for piracy availability leads to the finding that 287 of the 302 titles (95.03%) had torrent files uploaded to at least one of the three torrent sites before January 27, 2016, suggesting that the second assumption about piracy availability generally holds. The 15 titles that lack piracy availability are largely unpopular titles, as indicated by the relatively small monthly search volume per title per country (215.24) compared with the population mean (1214.67).

E.2. Ruling out an alternative explanation for the smaller effect for original titles

An alternative explanation for the smaller effect of Netflix's unavailability on piracy search for original titles relates to the second assumption about piracy availability discussed in E.1. If most original titles were not available on piracy sites, the unavailability of Netflix would not significantly affect consumers' piracy search for original titles, as consumers likely expected that there was little, if any, piracy supply for original titles. As 10 of the 15 titles that do not have torrents uploaded before January 27, 2016 are Netflix originals, we cannot directly rule out this explanation. If the market expansion, rather than the lack of piracy availability, is the main force driving the smaller effect for original than nonoriginal titles, we expect to find similar effect sizes for original and nonoriginal titles after we exclude these 15 titles without piracy availability from the sample. Following this reasoning, we conducted a robustness check using the sample of 287 titles with piracy availability. The results are qualitatively similar to what we found in the main analysis. The main effect of Netflix's unavailability in Indonesia on piracy search is 0.200. The post-/pretreatment MSPE ratio for Indonesia is 13.44, which ranks 1 out of 41 countries. Table E.1 and Table E.2 report the weight allocations across control countries and the pretreatment fit. The trend and gap plots of piracy search volume between the actual Indonesia and the synthetic Indonesia are close to Figure 3 and Figure 4, and therefore are omitted. Using a DiD-type method described in Section 5.4.1, the effect for original titles is 0.045 and the effect for nonoriginal titles is 0.240, which are also close to what we found in the main analysis. The results from this robustness check suggest that the smaller effect for original than nonoriginal titles is more likely driven by the existence of market expansion effect than by the lack of piracy supply for original titles.

E.3. Additional evidence for the market expansion effect

We provide further evidence for the market expansion effect by assessing the moderating effect of the release date of original titles. If the introduction of a legal distribution channel can expand the piracy market through increased WOM and promotion, we expect such a market expansion effect to be stronger for more recently released content because the effects of WOM and promotion tend to decay over time (Liu 2006, Sethuraman et al. 2011). To test the moderating effect of the release date, we median-split 49 original titles into two groups according to the release date. The effect size for the newer original titles is 0.030 and the effect size for the older original titles is 0.138 based on the DiD-type method. The smaller effect for newer original titles is consistent with the greater market expansion effect for newer original titles due to more recently created WOM and promotion.

Table E.1. Country Weights in the Synthetic Indonesia Using 287 Titles with Piracy Availability

Country	Weight	Country	Weight	Country	Weight
Afghanistan	-	Laos	-	South Korea	-
Armenia	-	Macau	-	Sri Lanka	-
Azerbaijan	-	Malaysia	-	Taiwan	-
Bahrain	-	Maldives	-	Tajikistan	-
Bangladesh	-	Mongolia	-	Thailand	0.412
Bhutan	-	Myanmar	-	Timor-Leste	-
Brunei	-	Nepal	-	Turkey	-
Cambodia	-	Oman	-	Turkmenistan	-
Hong Kong	-	Pakistan	-	United Arab Emirates	-
India	0.078	Palestine	0.382	Uzbekistan	-
Iraq	-	Philippines	0.129	Vietnam	-
Kazakhstan	-	Qatar	-	Yemen	-
Kuwait	-	Saudi Arabia	-		
Kyrgyzstan	-	Singapore	-		

Table E.2. Mean of Pretreatment Characteristics Using 287 Titles with Piracy Availability

	Indonesia		Average of 40 Control Countries
	Real	Synthetic	
Piracy Search Volume	0.912	0.920	1.035
Title Search Volume	462,396	439,700	196,705
Interest in Netflix	89,067	73,383	39,154
Interest in General Piracy	92,637	181,332	77,831
Interest in Competitors	37,726	37,264	14,138
Internet Users (2014)	43,627,401	33,942,075	15,332,347
Internet Users (2015)	50,083,428	45,443,652	19,182,586

Online Appendix F. Robustness Check of Synthetic Control Method Using 701 Titles

When we consider all 701 titles (excluding *Catch Me If You Can* and *Piku*) that appeared in Indonesia's Netflix catalog in January 2016, the main effect of Netflix's unavailability in Indonesia on piracy search is 0.224. The post-/pretreatment MSPE ratio for Indonesia is 11.47, which ranks 2 out of 41 countries. Table F.1 and Table F.2 report the weight allocation across control countries and the pretreatment fit. Figure F.1 shows the trend and gap plots of piracy search volume between the actual Indonesia and the synthetic Indonesia. Using a DiD-type method described in Section 5.4.1, the effect for original titles is 0.012 and the effect for nonoriginal titles is 0.242. Findings from the main analysis (based on 302 titles) are therefore robust to the consideration of all titles.

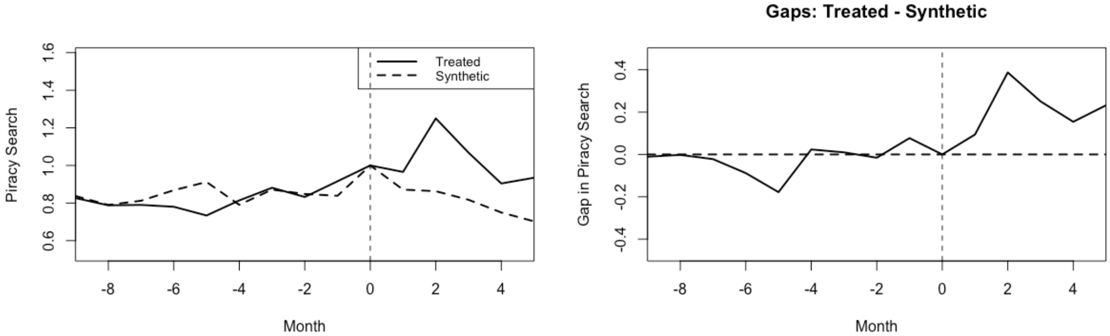
Table F.1. Country Weights in the Synthetic Indonesia Using 701 Titles

Country	Weight	Country	Weight	Country	Weight
Afghanistan	-	Laos	-	South Korea	-
Armenia	-	Macau	-	Sri Lanka	-
Azerbaijan	-	Malaysia	0.313	Taiwan	-
Bahrain	-	Maldives	-	Tajikistan	-
Bangladesh	-	Mongolia	-	Thailand	0.002
Bhutan	-	Myanmar	-	Timor-Leste	-
Brunei	-	Nepal	-	Turkey	0.140
Cambodia	-	Oman	-	Turkmenistan	-
Hong Kong	-	Pakistan	-	United Arab Emirates	-
India	0.039	Palestine	0.432	Uzbekistan	-
Iraq	-	Philippines	0.070	Vietnam	0.001
Kazakhstan	-	Qatar	-	Yemen	-
Kuwait	-	Saudi Arabia	-		
Kyrgyzstan	-	Singapore	-		

Table F.2. Mean of Pretreatment Characteristics Using 701 Titles

	Indonesia		Average of 40 Control Countries
	Real	Synthetic	
Piracy Search Volume	0.910	0.915	1.036
Title Search Volume	468,524	483,786	199,861
Interest in Netflix	89,067	75,841	39,154
Interest in General Piracy	92,637	144,545	77,831
Interest in Competitors	37,726	37,313	14,138
Internet Users (2014)	43,627,401	25,020,500	15,332,347
Internet Users (2015)	50,083,428	30,963,140	19,182,586

Figure F.1. Trends and Gaps in Piracy Search Using 701 Titles



Online Appendix G. Robustness Check Using 292 Titles in Foreign Languages

Table G.1 reports 10 titles in local languages of 41 Asian countries. To ensure that the main findings are not affected by these titles, we apply the synthetic control method to the data of the remaining 292 titles. The results show that piracy search volume is 21.1% higher in Indonesia than in the synthetic control country after Netflix's failure to launch in Indonesia. The post-/pretreatment MSPE ratio for Indonesia is 17.24, which ranks 1 out of 41 countries. Using a DiD-type method described in Section 5.4.1, the effect for original titles is 0.046 and the effect for nonoriginal titles is 0.256. The main findings are therefore not sensitive to the exclusion of these 10 titles.

Table G.1. Titles in Local Languages of 41 Asian Countries

Title	**Netflix Original**	**Language**
Akame Ga Kill!	No	Japanese
Gunslinger Girl	No	Japanese
Rurouni Kenshin	No	Japanese
Soul Eater	No	Japanese
Little Witch Academia	No	Japanese
Little Witch Academia: The Enchanted Parade	No	Japanese
Winx Club	No	Hindi
Heropanti	No	Hindi
Hum Aapke Hain Koun	No	Hindi
Maine Pyar Kiya	No	Hindi

Table G.2. Country Weights in the Synthetic Indonesia Using 292 Titles in Foreign Languages

Country	Weight	Country	Weight	Country	Weight
Afghanistan	-	Laos	-	South Korea	-
Armenia	-	Macau	-	Sri Lanka	-
Azerbaijan	-	Malaysia	-	Taiwan	-
Bahrain	-	Maldives	-	Tajikistan	-
Bangladesh	-	Mongolia	-	Thailand	0.407
Bhutan	-	Myanmar	-	Timor-Leste	-
Brunei	-	Nepal	-	Turkey	-
Cambodia	-	Oman	-	Turkmenistan	-
Hong Kong	-	Pakistan	-	United Arab Emirates	-
India	0.088	Palestine	0.409	Uzbekistan	-
Iraq	-	Philippines	0.095	Vietnam	-
Kazakhstan	-	Qatar	-	Yemen	-
Kuwait	-	Saudi Arabia	-		
Kyrgyzstan	-	Singapore	-		

Table G.3. Mean of Pretreatment Characteristics Using 292 Titles in Foreign Languages

	Indonesia		Average of 40 Control Countries
	Real	Synthetic	
Piracy Search Volume	0.880	0.890	1.038
Title Search Volume	442,603	409,854	187,139
Interest in Netflix	89,067	72,903	39,154
Interest in General Piracy	92,637	194,324	77,831
Interest in Competitors	37,726	37,119	14,138
Internet Users (2014)	43,627,401	34,902,230	15,332,347
Internet Users (2015)	50,083,428	47,496,300	19,182,586

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