Review of Economic Research on Copyright Issues, 2025, vol. 22, pp. 1-32

FROM BOOTLEG TO BINGE: USER MIGRATION AND LEGAL DEMAND FOLLOWING BRAZIL'S MEGAFILMESHD SHUTDOWN

BRETT DANAHER, JONATHAN HERSH AND MICHAEL D. SMITH

Abstract. In November 2015 the Brazilian Federal Police shut down *MegafilmesHD.net*, a piracy streaming site that accounted for roughly 60 million monthly visits – more traffic than any other piracy site in the country. We assemble a balanced click stream panel of 2,557 Brazilian Internet users and estimate a generalized difference in differences model to determine the effect of this shock on legal and illegal consumption. The event caused treated users to substitute to streaming piracy sites by 20% (minutes +61%) and, despite this diversion, raised their Netflix visits by 6% (minutes +11%). Because the panel includes self reported demographics, we shed light on *who* pivots after enforcement. Men, urban residents, and professional class users divert more heavily to alternative piracy sites, whereas income – constrained segments (students and the unemployed) are least likely to adopt paid streaming in response to the shutdown. Taken together, the evidence shows that even a single site shutdown can generate measurable legal uptake in an emerging market, but legal conversion is concentrated among higher income users. Price discrimination or ad supported versions of legal services may therefore complement enforcement by attracting the more price sensitive pirates.

1. Introduction

Digital piracy and its effect on legal marketplaces have been central topics in economics and information systems research for two decades. A growing empirical literature now measures how different anti-piracy policies – site blocking, graduated response, notice-and-takedown – shift consumption between illegal and legal channels (e.g., Adermon and Liang 2014; Aguiar et. al. 2018; Danaher et. al. 2020).

Yet we know far less about *who* changes behavior when a piracy supply shock occurs. Prior work profiles pirates demographically, but has not answered the more policy-relevant question: which users respond to enforcement by substituting into legal markets versus evading the policy? Pinpointing these margins of adjustment could help rights-holders and regulators target interventions more efficiently.

We address this gap by analyzing the November 2015 shutdown of MegafilmesHD.net – then Brazil's most visited piracy streaming/link site. While the event predates today's site-blocking waves in Brazil and other countries, domain-level shutdowns remain a primary enforcement tool worldwide; thus the mechanisms we identify continue to matter for current policy debates. Though MegafilmesHD was only a single piracy site, it provided a highly convenient way for Brazilian viewers to access pirated content, with an interface that used the Portuguese language and frequently pointed to pirated files containing Brazilian films or films with Portuguese subtitles or dubbing.

Analyzing a panel of the clickstream web browsing behavior of 2,557 Brazilian Internet users, we employ a generalized version of the difference-in-differences model following Card (1994) and, more recently, Danaher et. al. (2020). We find that the shutdown reduced visits to MegafilmesHD by over 90%, but it also induced a 20% increase in affected users' traffic to other similar piracy linking/streaming sites, with no shift towards piracy cyberlockers or P2P piracy sites. Importantly, treated users also raised their Netflix visits by 6% and time spent at Netflix by 11%, indicating some evidence of substitution into paid legal viewing.

Demographic heterogeneity is striking. Men and more educated individuals were more likely to locate and use alternative piracy sources, while women were more likely to curtail their piracy in response to the shutdown. Increases in Netflix usage were concentrated among those with higher disposable income: students and the unemployed showed statistically less legal uptake. These patterns likely highlight price sensitivity as a key barrier to migration from piracy to paid services.

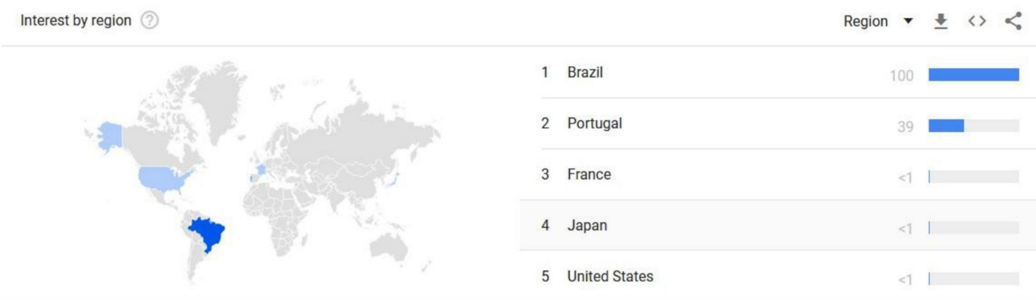
Our contribution is two-fold. First, we provide the first causal estimate of the impact of MegafilmesHD's shutdown on both substitute piracy and on paid streaming – extending the existing website-closure literature to a major emerging market and adding an important replication datapoint. Second, we uncover systematic demographic differences in post-shutdown behavior. Although we cannot identify the precise mechanism or reason for these differences (e.g. price sensitivity versus search costs), identifying *which* groups switch to legal channels and which persist in piracy is a necessary step toward designing more effective, targeted interventions – a topic to which we return in the concluding section.

2. Background

2.1. Film, Television, and Piracy in Brazil. According to the Motion Picture Association (MPA), Brazil ranked 11th in global box-office revenue in 2014 ($800 million) and was projected to grow to become the world's 4th largest audiovisual market over time given its pattern of rapid growth. Brazil also placed 8th in Video-on-Demand (VOD) revenue in 2016 ($352 million). Piracy, however, is pervasive in Brazil. An MPA-commissioned study identified 400 piracy websites tailored to Brazilian users; 57 of these sites drew more than one million monthly visitors and together offered 13,000 titles.[1] A piracy site is "tailored" to Brazil chiefly by using Portuguese interfaces, supplying Portuguese-subtitled or dubbed copies, and featuring locally produced films and TV shows.

2.2. MegafilmesHD.net Shutdown.

Figure 1: Google Trends Search Index for "MegafilmesHD" During 2014-2015



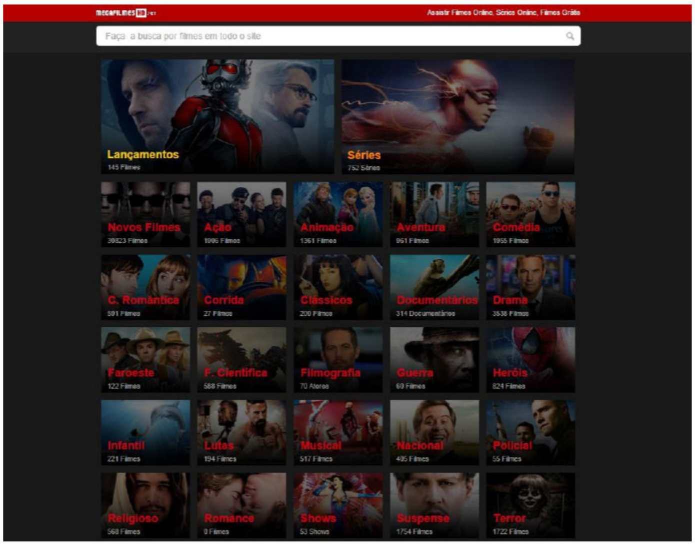
Notes: Note that the top country searching for MegafilmesHD was Brazil, with Portugal as a distant second (due to speaking the same language) and insignificant interest from any other countries. We use this to establish that MegafilmesHD was a piracy site catering specifically to Brazil (and to Portugal, to a lesser extent).

MegafilmesHD indexed roughly 150,000 links to infringing content – nearly all filmed, subtitled, or dubbed in Portuguese. By 2015, it ranked as the 48th most visited website in Brazil, attracting 60 million monthly visits.[2] Google Trends confirms its popularity was almost entirely domestic – see Figure 1.

[1] https://www.mpa-americalatina.org/wp-content/uploads/2018/06/MPAAL_10_04_2016-english-fv.pdf
[2] See https://torrentfreak.com/arrests-as-police-target-latin-americas-largest-pirate-site-151119

MegafilmesHD was characterized as a link-streaming piracy site. Unlike cyber-lockers (which host files) or P2P trackers (which coordinate peer-to-peer downloads), MegafilmesHD acted as a search and curation layer; it cataloged links hosted elsewhere and embedded them in a friendly, thumbnail-based interface in Portuguese. Clicking these links allowed one to easily stream the title in an embedded video player. Prior research shows that lower search costs can expand consumption and increase consumer surplus in digital markets (Brown and Goolsbee 2002; Brynjolfsson et. al. 2010, Nagaraj and Reimers 2023) and in piracy specifically (Rajavi et. al. 2024). Figure 2 illustrates the site's convenient Portuguese UI, simple search bar, and genre filters.

Figure 2: Main Search Page at MegafilmesHD Prior to Its Shutdown



On November 18th, 2015, the Brazilian Federal Police raided the locations hosting the servers behind MegafilmesHD; within days the domain went dark.[3] This takedown did *not* remove the underlying files from cyber-lockers, nor did it eliminate substitute link sites. Thus, two opposing hypotheses arise.

[3]https://iipa.org/files/uploads/2017/12/2016SPEC301BRAZIL.pdf

(1) *Disruption hypothesis* – if MegafilmesHD materially lowered search costs relative to other options, its removal could reduce overall piracy and prompt some users to pay for the convenience of legal services.
(2) *Substitution hypothesis* – Users may simply migrate to competing piracy link and/or streaming sites or search piracy cyberlockers directly, leaving total piracy and legal consumption unchanged.

Earlier evidence from other piracy shutdowns is mixed. While Danaher and Smith (2014) find that the shutdown of Megaupload.com cyberlocker site increased digital movie sales by 6.5-8.5%, Aguiar et. al. (2018) found no increase in legal consumption when Germany shut down kino.to, a piracy link/streaming site. This suggests that outcomes may depend on site prominence and convenience, or the local market context. Our study tests which scenario prevailed in Brazil.

2.3. **Netflix and Legal Consumption in Brazil.** During our study window, Netflix dominated Brazil's subscription video on demand (SVOD) market – industry estimates place its 2015-2016 share above 70%.[4] While we cannot observe box-office attendance or transactional VOD (e.g. iTunes downloads) in our data, we do record panelists' visits and minutes on Netflix.com. We therefore treat these metrics as proxies for paid legal viewing and ask: Did the shutdown shift any consumption toward Netflix? Is this effect stronger among any specific user segments?

3. Related Literature

3.1. **Digital Piracy and Sales of Information Goods.** A large empirical literature finds that piracy displaces legal demand. Danaher, Smith, and Telang (2017) review twenty-six peer reviewed publications and report that twenty-three of them document a negative effect of piracy on sales. For the Brazilian market in particular, Nishijima et. al. (2020) show that broadband-enabled piracy reduced box office revenues. Frick et. al.

[4]See, for example, https://www2.itif.org/2018-testimony-global-digital-trade.pdf or https://www.statista.com/statistics/867894/most-popular-video-on-demand-platforms-brazil/#statisticContainer

(2023) specifically show that piracy is an economic substitute for Netflix. These findings motivate research on whether enforcement can reverse such losses / substitution.

3.2. **Antipiracy Enforcement and Strategies.** Antipiracy enforcement actions can vary in scope and effectiveness. Demand-side notices or legal penalties can increase music sales when credibly enforced (Danaher et. al. 2014; Adermon and Liang 2014), but have little impact on movie box office (McKenzie 2017). Supply-side interventions yield mixed results. Seizing and shutting down Megaupload.com boosted digital movie sales by 6.5-8.5% and shifted box office revenues toward blockbusters and away from smaller, independent films (Peukert et. al. 2017). By contrast, blocking The Pirate Bay in the Netherlands and in the UK had limited effects on total piracy or legal consumption (Poort et. al. 2014; Danaher et. al. 2020). Aguiar et. al. (2018) find that shutting down Germany's link streaming site kino.to merely displaced piracy to substitute piracy sites with no legal uptick. Blocking 19 major piracy sites in the UK in 2013 and over 50 sites in 2014 both caused increases in legal consumption (Danaher et. al. 2020). The effectiveness of supply-side antipiracy interventions may therefore depend on the degree to which they increase the search and learning costs of piracy.

3.3. **Demographics, Psychology, and Piracy.** Evidence consistently shows that men and younger individuals pirate more than women and older cohorts (Kwong et. al. 2003; Mandel and Süssmuth 2012). Theoretical work attributes these patterns to cognitive dissonance (Festinger 1957; Redondo and Charron 2013) and neutralization techniques (Sykes and Matza 1957; Ingram and Hinduja 2008), which pirates use to rationalize illegal behavior. Survey evidence from Riekkinen (2016) suggests that men rely more on neutralization (e.g. "I only pirate because the industry charges so much" or "I wouldn't pirate if the industry didn't make it so hard to find content"), whereas women are more likely to practice cognitive dissonance (e.g. "piracy is not a 'real' crime" or "piracy is victimless").

What remains largely unexplored is whether these demographic and psychological differences translate into differential responses to enforcement. Reis et. al. (2024) provide the only causal evidence we are aware of, showing that DNS blocking reduced piracy less for households with younger members. We extend this line of inquiry by examining gender, education, and income heterogeneity following the MegafilmesHD shutdown, and by measuring both illegal substitution and legal uptake.

4. Data

4.1. **Panel Source and Construction.** We use clickstream data from Netquest, a market research panel that installs passive tracking software on the personal computers of consenting users. From the full panel we select the 2,557 Brazilian users who are observed continuously between August 18, 2015 and February 17, 2016 – exactly three months before and after the MegafilmesHD shutdown – yielding a balanced six month panel. Thus the shutdown occurred on the first day of the fourth month in our data.

For each user-month we observe the following: (i) visits and minutes on MegafilmesHD.net; (ii) aggregate visits/minutes to other link streaming piracy sites, cyberlocker/host piracy sites, and P2P tracker piracy sites; (iii) visits/minutes to Netflix.com, the dominant legal SVOD service. Site lists for each piracy bucket are in Appendix A, and the construction protocol is described in Appendix B. All variables are measured as total monthly counts, and we treat each panelist with equal weight.

4.2. **Descriptive Statistics.** Table 1 reports means and standard deviations. As is common with web traffic, distributions are highly right-skewed. Pre-shutdown, MegafilmesHD averaged 3.28 monthly visits per user, exceeding any single piracy site and rivalled only by Netflix (3.56 monthly visits per user). Streaming/link piracy sites dominate minutes because users watch videos in-browser or in a video player while on the site, while P2P and cyberlocker sites mainly facilitate downloads.

Table 1: Summary Statistics Average Monthly Media Sites Visits Before/After Blocking

	Before Megafilmes Shutdown		After Megafilmes Shutdown	
	mean	sd	mean	sd
Megafilmes Visits	3.28	11.32	0.33	1.04
Minutes Spent on Megafilmes	56.77	293.36	0.82	6.11
Host Piracy Sites Visits	1.48	3.43	1.29	2.99
Peer-to-Peer Sites Visits	0.42	2.09	0.69	2.74
Link Piracy Sites Visits	2.75	9.71	4.74	13.46
Paid Subscription Sites Visits	3.56	11.28	4.56	13.80
Minutes Spent on Host Piracy Sites	4.24	17.91	3.28	11.05
Minutes Spent on Peer-to-Peer Sites	0.72	5.16	1.51	11.14
Minutes Spent on Link Piracy Sites	27.64	117.89	49.41	195.88
Minutes Spent on Paid Subscription Sites	57.55	261.78	80.44	328.34
Individuals	2557		2557	

Post-shutdown, traffic to MegafilmesHD collapses (-90% visits, -99% minutes),[5] confirming the effectiveness of the takedown. Visits to other link/streaming sites rise by ~70%, while Netflix visits increase more modestly (about one extra visit per month, and a 40% increase in minutes). These raw changes motivate the causal analysis but are not themselves determinative, given pre-existing regional growth in Netflix adoption.

4.3. **Treatment Intensity.** Our identification strategy exploits heterogeneity in pre-shutdown usage of MegafilmesHD, which we use as a proxy for the "bite" of the treatment on a given user. Notably, this is the same identification strategy used in Danaher et. al. (2020) to study the effect of the 2012, 2013, and 2014 waves of piracy website blocks in the UK. The intuition is that users who did not visit MegafilmesHD during the pre-period likely would not have attempted to do so in the post-period, making them similar to a control group. Heavy users of MegafilmesHD during the pre-period were likely more affected by the treatment than lighter users. This intuition backs our implementation of the

[5]The remaining visits occurred in the first month of the post-shutdown period, when some tech/piracy blogs reported the site had sporadic uptime but with limited piracy link availability. https://torrentfreak.com/arrests-as-police-target-latin-americas-largest-pirate-site-151119/

generalized difference-in-differences model with a continuous metric of treatment intensity – namely, the user's pre-period visits to MegafilmesHD.

Table 2 shows that 60% of users never visited MegafilmesHD (the "control" group), while the treated 40% display wide variation in pre-shutdown usage – from occasional browsers (≤ 5 visits/month) to heavy users (> 50 visits/month). This dispersion provides the continuous treatment intensity required for our generalized difference-in-differences estimator.

Table 2: Frequency Distribution for Pre-Shutdown Visits to MegaFilmesHD

Pre-Shutdown Visits to MegafilmesHD	Frequency
0	1549
1-4	455
5-9	122
10-24	166
25-49	113
50-99	99
100+	53

4.4. **Demographic Covariates.** Netquest collects self-reported demographics: gender, age, urban/suburban/rural location, socio-economic class, employment and student status, number of children, and whether the respondent is the primary earner. Following the literature review, we focus on gender, student status, and age as theoretically relevant moderators, and additionally we use socio-economic class, employment status, and urban residence as proxies for income and education, neither of which are directly observable in our data. We also consider the number of children in the household given results from the prior literature (Reis et. al. 2024). Table 3 summarizes the sample: 52% female; 47% located in Brazil's two largest metro areas; 8% students; 10% unemployed; and 29% in the professional class.

5. Empirical Model and Results

5.1. **Overall Effect of the Shutdown.** Descriptive statistics in Table 1 show traffic shifts after the MegafilmesHD raid, but simple before-after comparisons cannot separate the policy effect from underlying trends, such as the secular rise of Netflix in Brazil. We therefore exploit individual heterogeneity in pre-shutdown usage of MegafilmesHD to estimate the causal impact.

Let $Pre\_Megavisits_i$ denote the number of visits user i made to MegafilmesHD during the three months before the takedown. We treat this as a continuous measure of treatment intensity; users with $Pre\_Megavisits_i = 0$ form a control group, while heavier users experienced a larger "bite" of the policy than lighter users. The key identifying assumption is parallel trends in intensity: we must assume that, absent the shutdown, changes in visits to any outcome site would be uncorrelated with $Pre\_Megavisits_i$.

We first estimate a month-by-month event-study:

$$visits_{it} = \beta_0 + \beta_1 Pre\_Megavisits_i + \sum_{t=1}^{6} \beta_2 Month_t + \beta_3 Month_t \times Pre\_Megavisits_i + \mu_i + \varepsilon_{it} \tag{1}$$

where $visits_{it}$ represents the number of visits made by individual i during month t to the outcome sites (any of the buckets of remaining piracy sites, or Netflix), $Month_t$ represents a vector of month fixed effects, $Pre\_Megavisits_i$ is the treatment intensity of user i, μ_i is a vector of individual fixed effects, and ε_{it} is a stochastic error term. β_3 is the coefficient of interest. We omit $month\ t = 3$ as it is the month just before treatment. The β_3 coefficients trace how month-to-month changes in outcome visits vary with treatment intensity. Our outcome variable – $visits$ – is a count variable with relatively low counts and with over-dispersion. We therefore estimate (1) with the conditional fixed effects negative binomial estimator (FE-NB) of Hausman, Hall, and Griliches (1984), which avoids the incidental parameters bias associated with unconditional fixed effects negative binomial models.[6]

Figure 3: Monthly Coefficients From Table 5 Showing Impact of MegafilmesHD Blocking on Visits to Piracy Sites and Netflix

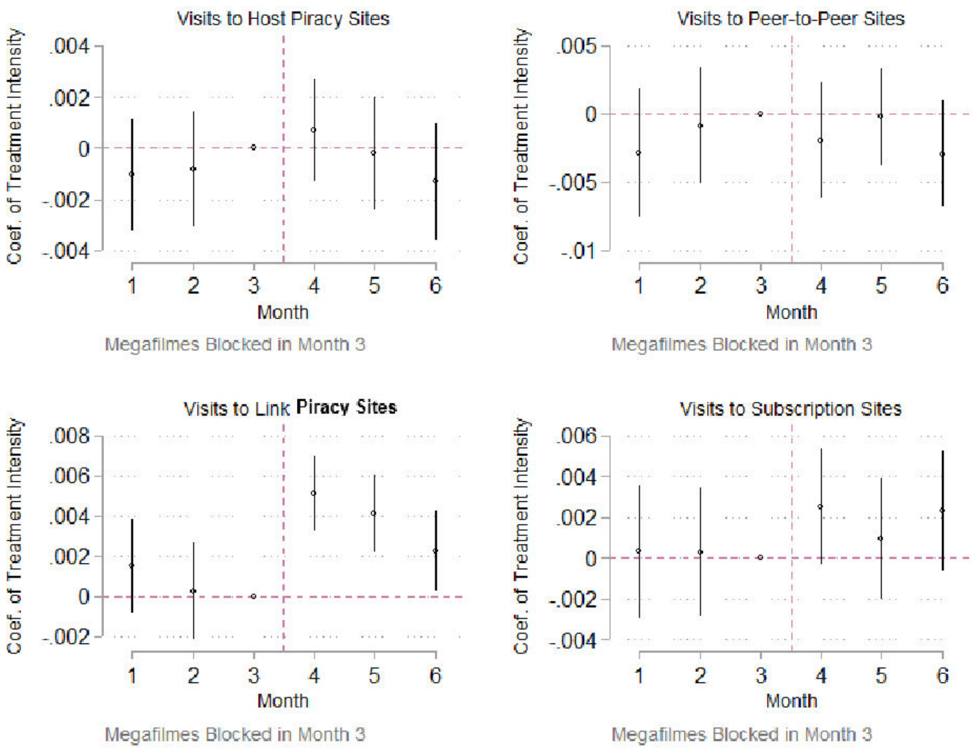


Figure 3 plots β_3 for each outcome. Pre-period coefficients ($t = 1, 2$) are indistinguishable from zero, supporting the parallel trends assumption for all outcomes. Post-shutdown, β_3 are also indistinguishable from zero for remaining P2P and cyberlocker piracy sites, implying no diversion to those channels. β_3 are positive and statistically significant for other link/streaming piracy sites in months 4-6, though this declines some over time. This could be the result of thwarted MegafilmesHD users visiting a number of piracy link sites shortly after the shutdown to find ones that work for them, and then settling into those sites. Finally, β_3 are positive but individually insignificant for Netflix visits, yet a Wald

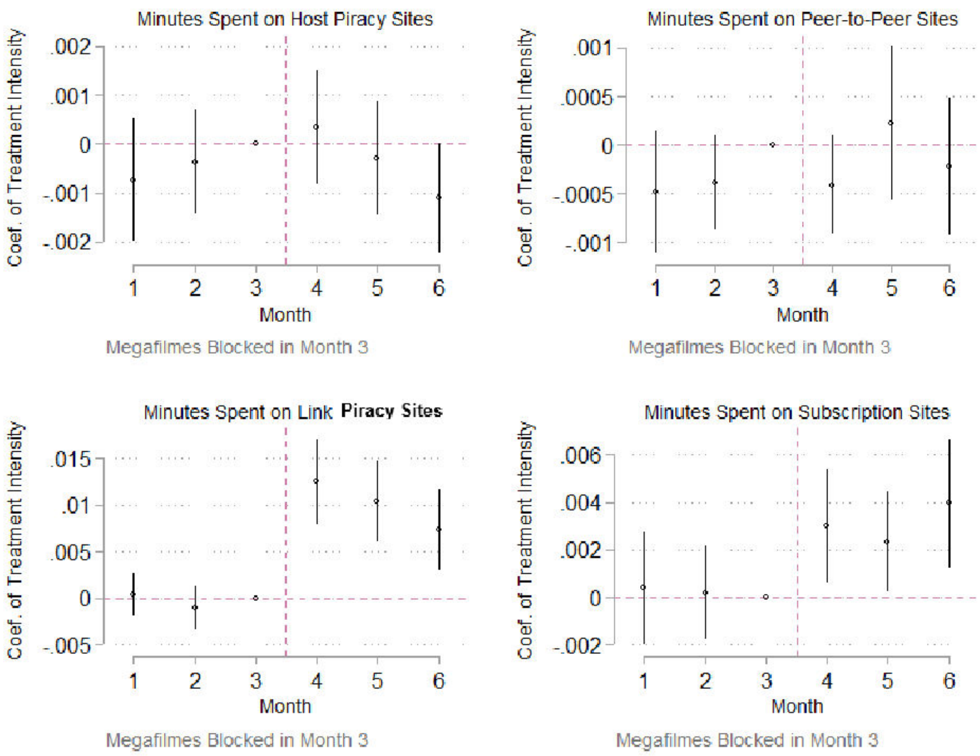
---

[6]The conditional NB estimator does not estimate a true fixed effect and therefore retains time-invariant covariates – for example, $Pre\_Megavisits_i$.

test rejects the null hypothesis that these coefficients are jointly equal to zero for months 4-6 ($p < 0.05$).

Repeating the analysis with $\ln(minutes + 1)$ as the outcome and a standard fixed effects OLS estimator[7] (Figure 4) yields similar patterns, with β_3 individually significant for Netflix in all post-shutdown months. Coefficient estimates supporting Figures 3 and 4 can be found in Tables 5-6.

Figure 4: Monthly Coefficients From Table 5 Showing Impact of MegafilmesHD Blocking on Minutes Spent Piracy Sites and Netflix



[7]Cameron and Trivedi (2005) suggest generalized linear models like negative binomial for count data when the expected value is below ten (as it is with visits) but using OLS when it is ten or above (as it is for minutes).

Table 5: Impact of MegafilmesHD Blocking on Legal and Illegal Website Visits

Site Type Dependent Variable	Pre-Post Blocking	**Host Piracy** *Visits*	**Peer-to-Peer** *Visits*	**Link Piracy** *Visits*	**Paid Subscription** *Visits*
month=1		-0.0152	0.0207	-0.149*	-0.101
		(0.0441)	(0.0935)	(0.0579)	(0.0633)
month=2		-0.0287	0.00420	-0.103+	-0.0307
		(0.0446)	(0.0924)	(0.0576)	(0.0624)
month=3			*Omitted base case*		
month=4		-0.158***	0.153+	0.398***	0.136*
		(0.0454)	(0.0908)	(0.0511)	(0.0600)
month=5		-0.188***	0.733***	0.419***	0.372***
		(0.0459)	(0.0812)	(0.0513)	(0.0583)
month=6		-0.149**	0.826***	0.356***	0.305***
		(0.0455)	(0.0809)	(0.0523)	(0.0594)
Treat Intensity: Pre-Period Visits to Megafilmes		0.000146	0.00231	-0.000211	-0.00333**
		(0.00107)	(0.00220)	(0.000963)	(0.00126)
month=1 # Treat Intensity: Pre-Period Visits to Megafilmes	Pre	-0.00104	-0.00284	0.00149	0.000324
		(0.00111)	(0.00240)	(0.00119)	(0.00165)
month=2 # Treat Intensity: Pre-Period Visits to Megafilmes	Pre	-0.000799	-0.000869	0.000246	0.000285
		(0.00114)	(0.00219)	(0.00124)	(0.00159)
month=3 # Treat Intensity: Pre-	Pre		*Omitted base case*		
month=4 # Treat Intensity: Pre-Period Visits to Megafilmes	Post	0.000720	-0.00193	0.00511***	0.00250+
		(0.00102)	(0.00220)	(0.000948)	(0.00142)
month=5 # Treat Intensity: Pre-Period Visits to Megafilmes	Post	-0.000203	-0.000234	0.00411***	0.000933
		(0.00112)	(0.00181)	(0.000969)	(0.00149)
month=6 # Treat Intensity: Pre-Period Visits to Megafilmes	Post	-0.00130	-0.00291	0.00225*	0.00230
		(0.00115)	(0.00198)	(0.00103)	(0.00150)
Constant		0.0524	-0.703***	-0.819***	-0.761***
		(0.0450)	(0.0828)	(0.0473)	(0.0523)
N		10440	4212	9408	7344
Individuals		1740	702	1568	1224
Log-Likelihood		-11335.85	-4077.75	-13383.43	-10101.15
Month FEs		Y	Y	Y	Y
Individual FEs		Y	Y	Y	Y
Estimator		Negative Binomial Count	Negative Binomial Count	Negative Binomial Count	Negative Binomial Count

Standard errors in parentheses
*** p < 0.001 ** p < 0.01 * p < 0.05 + p < 0.1

Table 6: Impact of MegafilmesHD Blocking on Minutes Spent at Legal and Illegal Media Websites

Site Type / Dependent Variable	Pre-Post Blocking	(1) **Host Piracy** *Log of Minutes*	(2) **Peer-to-Peer** *Log of Minutes*	(3) **Link Piracy** *Log of Minutes*	(4) **Paid Subscription** *Log of Minutes*
month=1		-0.0116	0.00297	-0.0449	-0.0626*
		(0.0231)	(0.0106)	(0.0290)	(0.0295)
month=2		-0.0221	-0.00873	-0.0381	-0.0349
		(0.0215)	(0.00884)	(0.0269)	(0.0241)
month=3			*Omitted base case*		
month=4		-0.0585**	0.0141	0.188***	0.0603*
		(0.0206)	(0.00972)	(0.0321)	(0.0271)
month=5		-0.0750***	0.121***	0.261***	0.209***
		(0.0221)	(0.0135)	(0.0352)	(0.0334)
month=6		-0.0719**	0.135***	0.177***	0.155***
		(0.0226)	(0.0142)	(0.0358)	(0.0358)
month=1 # Treat Intensity: Pre-Period Visits to Megafilmes	Pre	-0.000728	-0.000479	0.000441	0.000399
		(0.000642)	(0.000318)	(0.00118)	(0.00120)
month=2 # Treat Intensity: Pre-Period Visits to Megafilmes	Pre	-0.000367	-0.000385	-0.000995	0.000195
		(0.000547)	(0.000250)	(0.00118)	(0.000990)
month=3 # Treat Intensity: Pre-Period Visits to Megafilmes	Pre		*Omitted base case*		
month=4 # Treat Intensity: Pre-Period Visits to Megafilmes	Post	0.000329	-0.000409	0.0125***	0.00300*
		(0.000592)	(0.000258)	(0.00234)	(0.00122)
month=5 # Treat Intensity: Pre-Period Visits to Megafilmes	Post	-0.000299	0.000226	0.0104***	0.00231*
		(0.000590)	(0.000402)	(0.00220)	(0.00107)
month=6 # Treat Intensity: Pre-Period Visits to Megafilmes	Post	-0.00110+	-0.000217	0.00732***	0.00396**
		(0.000573)	(0.000358)	(0.00221)	(0.00138)
Constant		0.551***	0.120***	0.770***	0.740***
		(0.0137)	(0.00700)	(0.0193)	(0.0182)
N		15342	15342	15342	15342
Individuals		2557	2557	2557	2557
Within-R2		0.002	0.025	0.052	0.014
Between-R2		0.001	0.001	0.153	0.015
Estimator		Panel OLS	Panel OLS	Panel OLS	Panel OLS

Standard errors in parentheses, clustered at individual level.
*** $p < 0.001$ ** $p < 0.01$ * $p < 0.05$ + $p < 0.1$

To summarize the total post-shutdown effect we collapse months 4-6 into a single $Post_t$ indicator:

$$visits_{it} = \beta_0 + \beta_1 Post_t + \beta_2 Pre\_Megavisits_t + \beta_3 Post_t \times Pre\_Megavisits_i + \mu_i + \varepsilon_{it} \quad (2)$$

Here, β_3 is our coefficient of interest. Table 4 reports estimates for both outcomes (visits and log minutes) for each bucket of sites.

Table 4: Effect of MegafilmesHD Website Blocking on Substitution To Legal and Illegal Channels, Generalized Difference-in-Differences

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Site Type	**Host Piracy**	**Peer-to-Peer**	**Link Piracy**	**Paid Subscription**	**Host Piracy**	**Peer-to-Peer**	**Link Piracy**	**Paid Subscription**
Dependent Variable	*Visits*	*Visits*	*Visits*	*Visits*	*Log of Minutes*	*Log of Minutes*	*Log of Minutes*	*Log of Minutes*
Post = 1 if after MegafilmesHD blocked	-0.151***	0.581***	0.471***	0.315***	-0.0572***	0.0919***	0.236***	0.174***
	(0.0265)	(0.0485)	(0.0303)	(0.0344)	(0.0141)	(0.00887)	(0.0263)	(0.0250)
Treat Intensity: Pre-Period Visits to Megafilmes	-0.000574	0.000619	0.0000849	-0.00310***				
	(0.000875)	(0.00172)	(0.000618)	(0.000817)				
Pre-Period Visits to Megafilmes x Post	0.000401	-0.000369	0.00333***	0.00170*	0.00000796	0.000155	0.0102***	0.00289**
	(0.000657)	(0.00121)	(0.000556)	(0.000847)	(0.000308)	(0.000229)	(0.00208)	(0.00112)
Constant	0.0396	-0.744***	-0.900***	-0.812***	0.536***	0.115***	0.740***	0.710***
	(0.0374)	(0.0616)	(0.0341)	(0.0373)	(0.00681)	(0.00437)	(0.0123)	(0.0125)
N	10440	4212	9408	7344	15342	15342	15342	15342
Individuals	1740	702	1568	1224	2557	2557	2557	2557
Log-Likelihood	-11338.92	-4130.59	-13404.34	-10112.65				
Within-R2					0.002	0.014	0.049	0.012
Between-R2					0.001	0.001	0.153	0.015
Individual FEs	Y	Y	Y	Y	Y	Y	Y	Y
Estimator	Negative Binomial Count	Negative Binomial Count	Negative Binomial Count	Negative Binomial Count	Panel OLS	Panel OLS	Panel OLS	Panel OLS

Standard errors in parentheses, clustered at individual level for Panel OLS models.
*** p < 0.001 ** p < 0.01 * p < 0.05

In columns (1) through (4), we observe no significant effect of the shutdown on visits or minutes on P2P or cyberlocker piracy sites. We observe a statistically significant ($p < 0.001$) increase in link piracy site visits such that for each additional pre-period visit to MegafilmesHD, a user increased post-period visits to substitute link piracy sites by an additional 0.33%. We observe a smaller but statistically significant ($p < 0.05$) increase in visits to Netflix, such that a user with one more pre-period visits to MegafilmesHD increased her visits to Netflix by 0.17%. Together, these estimates indicate that shutting down MegafilmesHD diverted a sizeable fraction of its users to other link piracy sites and a smaller but significant share toward legal SVOD consumption.

While we prefer the NB model for visits and OLS for minutes, the conditional FE-NB model does not allow for clustering of standard errors at the user level. In Appendix C we validate the significance of our results using traditional fixed effects OLS estimation with $\ln(visits + 1)$ as the dependent variable, and we cluster standard errors at the individual level. All key results remain the same in sign and significance, supporting our FE-NB inferences.

In columns (5) through (8) of Table 4 we observe similar results for minutes spent on the outcome sites. In Appendix C we show that these OLS results for minutes hold under the conditional FE-NB model as well.

5.2. **Do Economic or Demographic Factors Dominate Piracy Decisions Post-Shutdown?** Having shown that the raid and shutdown shifted behavior on average, we next ask which user groups drove those changes. We interact treatment intensity with one demographic covariate at a time:

$$\begin{aligned} visits_{it} &= \beta_0 + \beta_1 Post_t + \beta_2 Pre\_Megavisits_i + \beta_3 Post_t \times Pre\_Megavisits_i \\ &\quad + \beta_4 Demographic\_Moderator_i \times Post_t \times Pre\_Megavisits_i \\ &\quad + \beta_5 Demographic\_Moderator_i + \beta_6 Post_t \times Demographic\_Moderator_i \\ &\quad + \beta_7 Demographic\_Moderator_i \times Pre\_Megavisits_i + \mu_i + \varepsilon_{it} \end{aligned} \tag{3}$$

Where $Demographic\_Moderator_i$ is a binary indicator ($female = 1$, $student = 1$, $age\_over\_35 = 1$, etc).[8] While β_3 indicates the effect of the shutdown when the indicator is set to zero, the triple interaction coefficient β_4 (the coefficient of interest) measures whether the post-shutdown response varies across the demographic dimension. We estimate (3) with the same conditional FE-NB specification used in section 5.1, and we repeat these analyses with $\ln(minutes + 1)$ as the outcome variable using panel OLS with robust

[8] The only exception is the "children" variable, which is a count of the number of children in the household.

clustered standard errors. For parsimony we restrict attention to the two outcomes that exhibited mean effects: other link piracy sites, and Netflix.

Figure 5 (visits) and Figure 6 (minutes) plot β_4 with 95% confidence intervals; full tables appear in Appendix C (Tables C3-C6). Below we summarize the patterns and interpret them with appropriate caution given the limited scale of our data and our limited statistical power.

Figure 5: Regression Summary, Moderating Impact of Demographic Group on Link Piracy Sites and Netflix Visits in Response to Website Blocking

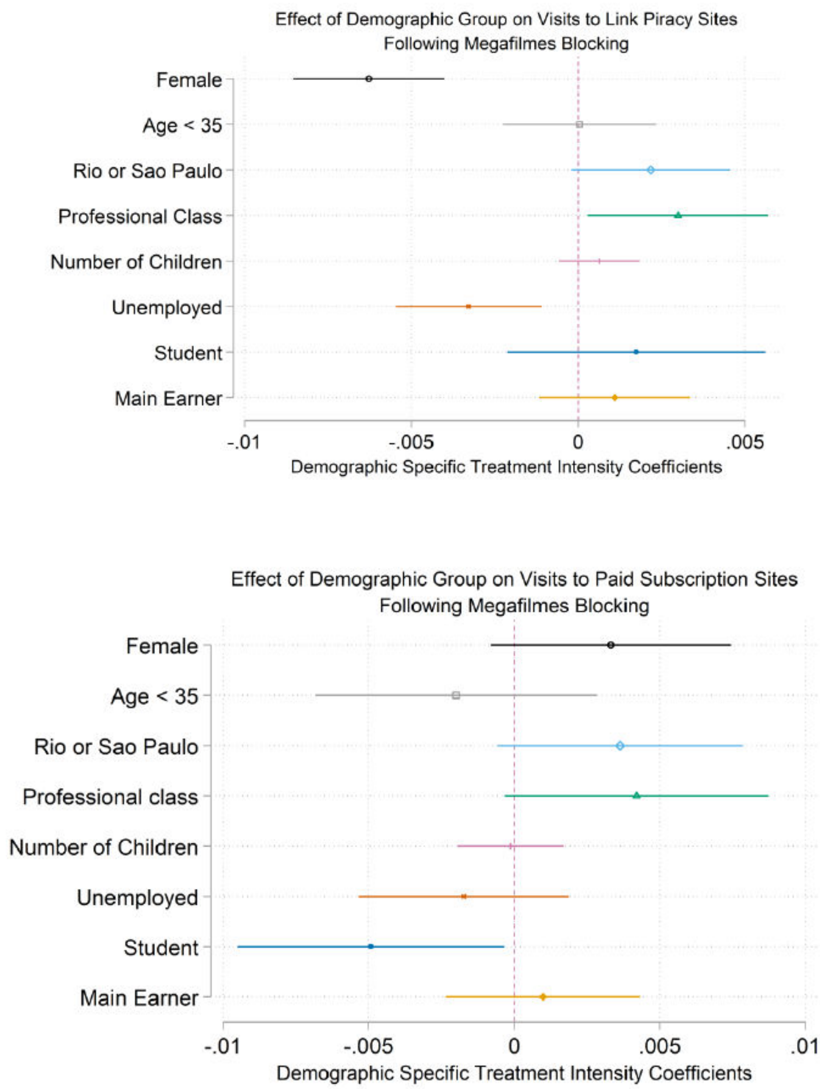
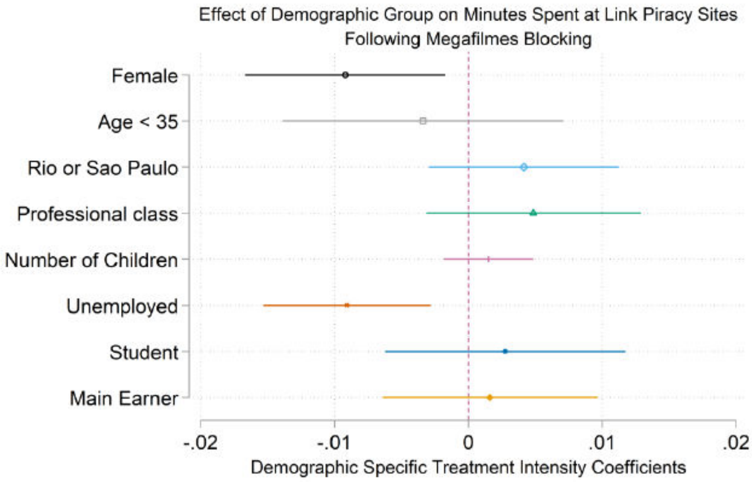
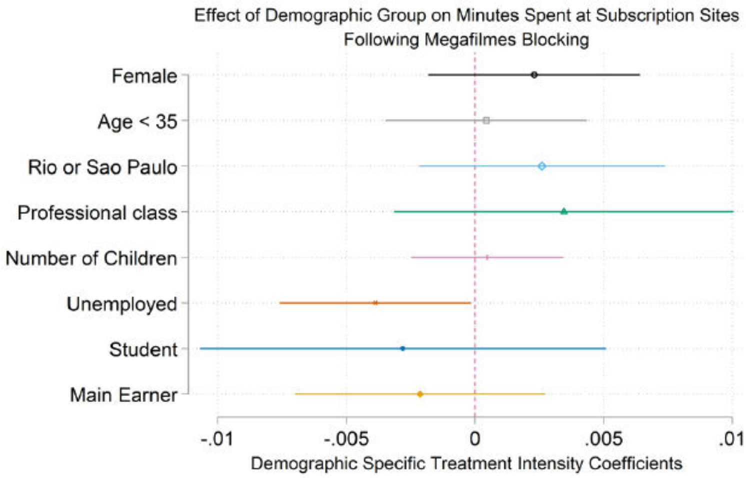


Figure 6: Regression Summary, Moderating Impact of Demographic Group on Minutes Spent on Link Piracy Sites and Netflix in Response to Website Blocking





5.2.1. *Gender.* Female users exhibit a significantly smaller diversion to substitute link sites ($p < 0.05$) for both minutes and visits. Females are also more likely to switch to Netflix after the shutdown, but this result is not statistically significant ($p = 0.12$). This result is consistent with survey evidence that women are less willing to sustain piracy once illegality is salient (cognitive dissonance mechanism) while men are more likely to react to an enforcement by doubling down on piracy (antipiracy enforcement exacerbates neutralization). We refrain from claiming that women necessarily shift more to legal channels – the evidence suggests this, but it is statistically weak.

5.2.2. *Student Status.* The point estimates indicate that students increase visits (and minutes) to substitute link piracy sites more than non-students, but this effect is imprecisely estimated ($p > 0.1$). For Netflix, however, the student interaction is negative and marginally significant (*visits* $p = 0.09$, *minutes* $p = 0.11$). Taken together, the data weakly support the idea that students are less responsive to enforcement – either because of lower income or stronger peer norms – but the evidence is not conclusive.

5.2.3. *Socio-economic Class, Employment, and Urbanity.* Professional class and urban residents – proxies for both higher education and income – show a larger diversion to other link piracy sites ($p < 0.05$ and $p < 0.1$, respectively). The unemployed divert less to other piracy sites ($p < 0.01$) but they also divert fewer minutes ($p < 0.05$) to Netflix and possibly fewer visits ($p > 0.1$) as well.

These patterns suggest that search and switching costs - which fall with education and digital literacy - dominate the decision to keep pirating after a site is shut down. By contrast, income constraints dominate the decision to pay for legal services, implying that price sensitive pirates are least likely to convert unless lower cost tiers are available. We acknowledge that education and income are conflated in our proxies – future work with direct measures could better disentangle these two mechanisms.

5.2.4. *Age, Main Earner, and Children.* None of these variables moderate post-shutdown changes for either piracy or Netflix, suggesting that age-based stereotypes about piracy persistence do not hold in this context (contrary to Reis et. al. 2024). Whether one is the main earner/financially responsible for household services also did not appear to moderate a user's reaction to the shutdown.

5.2.5. *Caveats.* These demographic findings come with several caveats. First, we report unadjusted p-values for each test, in spite of having conducted multiple hypothesis tests. Controlling for false discovery rates might render some of these results statistically indistinguishable from zero. Generally, significance may be limited due to the sample size of 2,557 users; some sub-groups (e.g. students, unemployed) are small which necessarily widens confidence intervals. As well, while the patterns align with cognitive dissonance, search cost theories, and income constraints, we cannot directly observe rationalizations, effort, or price elasticity. In light of these caveats, we interpret the demographic heterogeneity as *consistent with* – and not *proof of* – those mechanisms.

5.3. **New Subscribers.** Thus far, our models have asked whether the MegafilmesHD shutdown increased visits to Netflix and we have shown a causal increase. One might ask whether this increase is simply due to pre-existing subscribers – who also pirated at MegafilmesHD – increasing their visits to Netflix as a result of the shutdown, or if the shutdown actually caused new paid subscriptions.

We only have data on visits to and minutes at Netflix, and we lack data on subscriber status or payments. However, we can explore this question with some assumptions. We first eliminate the 838 users in our data who made any visits to Netflix during the pre-period months, under the assumption that the remaining 1,719 users were non-subscribers to Netflix during the pre-period. We then generate a variable $Post\_Subscriber_i$ equal to 1 if user i made at least one Netflix visit during the post-period. Our assumption is that this indicates a new subscription, though we also test sensitivity by requiring at least 2 or at least 3 Netflix visits in the post-period to indicate a new subscription. We then estimate:

$$Post\_Subscriber_i = \beta_0 + \beta_1 Pre\_Megavisits_i \tag{4}$$

Because $Post\_Subscriber_i$ is a binary outcome, we estimate the model using a logit specification and we report the results in Table 7. There are no user fixed effects because we have already conditioned on all users in the specification being non-users of Netflix during the pre-period.

Table 7: Effect of Shutdown on Prob(subscribe)

# Post-Period Visits to Indicate Subscription	>0 *Visits*	>1 *Visits*	>2 *Visits*
Treat Intensity	0.0058***	0.0069***	0.0062***
	(0.0017)	(0.0018)	(0.0018)
Constant	-1.2935***	-2.0738***	-2.3819***
	(0.0603)	(0.0781)	(0.0880)
N	1719	1719	1719
Individuals	1719	1719	1719
Log-Likelihood	-909.07	-620.38	-514.84
Estimator	Logit	Logit	Logit

Standard errors in parentheses
*** $p < 0.001$ ** $p < 0.01$ * $p < 0.05$ + $p < 0.1$

The first column assumes that at least one post-period Netflix visit indicates a new subscriber, while the second requires at least two visits and the third requires 3 or more visits to indicate a new Netflix subscription.

The coefficient of interest, β_1, is positive and statistically significant across all columns. The probability that someone became a subscriber during the post period is positively related to how much they used MegafilmesHD before it was shut down. While this model is not perfect, the fact that more intense users of MegafilmesHD were more likely to convert from non-use of Netflix to becoming a subscriber suggests a likely causal link. Thus, under our identifying assumptions, the evidence indicates that at least some portion of the increase in usage of Netflix caused by the shutdown came from new, paid users.

6. Discussion

6.1. **How Large Was the Shock?** MegafilmesHD was the single most visited piracy domain in our panel – 40% of users accessed it at least once in the three months before the raid. Shutting the site down led to statistically significant increases in visits and minutes at both other link piracy sites and at Netflix. By pairing the coefficient estimates from Table

4 with each user's treatment intensity, we can calculate each user's counterfactual visits to these sites in the absence of the shutdown (i.e. if treatment intensity were zero). Thus, we can compute each user's causal change in outcome visits and minutes to aggregate an overall back-of-the-envelope effect on treated users.

We conclude that, relative to a no shutdown counterfactual, the average treated user increased their visits to other remaining link piracy sites by 20% and minutes at these sites by 61%. These results are consistent with the German shutdown of kino.to, where Aguiar et. al. (2018) found that pirates dispersed to other sites after the shutdown.

However, we also find that the shutdown caused treated users to increase their visits to Netflix by 6% and their time spent at Netflix by 11%, on average. These results contradict the kino.to results where there was no uptick in legal, but the authors of that study note that only 17% of users visited kino.to before the shutdown, while 40% of users in our data visited MegafilmesHD. Our findings are similar to the legal increases when Megaupload was shutdown (6.5-8.5%) and during the UK's multi-site piracy blockade (7-12% increase). (Danaher and Smith 2014; Danaher et. al. 2020). In general this underscores the role of site prominence and market context in determining the expected effect of an antipiracy intervention on legal consumption.

Of particular note, we also find that treatment intensity positive correlated with the probability that a user became a first time visitor (and presumably subscriber) to Netflix following the shutdown, suggesting that some fraction of the increase in Netflix visits can be explained by new paying subscribers..

6.2. **Who Persists in Piracy and Who Converts?** The triple interaction estimates in Section 5 reveal three broad patterns.

(1) *Gender* – Female users divert markedly less traffic to substitute link piracy sites than male users in both visits and minutes. Female users are also more likely to increase usage of Netflix, but this result is not statistically significant ($p = 0.12$). The overall evidence is consistent with the notion that women are more likely to

abandon piracy when illegality becomes salient, and it suggests that they may be more likely to migrate to paid legal consumption.

(2) *Student Status* – Students are more likely to add traffic to alternative link piracy sites, although the estimates are imprecise ($p > 0.1$). Their uptake of Netflix is smaller than non-students; the interaction is negative and marginally significant for visits ($p = 0.09$) and minutes ($p = 0.11$). This pattern is directionally consistent with lower disposable income or stronger peer norms among students, but it should be viewed as suggestive.

(3) *Socioeconomic Class, Employment, Urbanity* – Users in the professional class and those living in urban centers – proxies for education and income – show a larger diversion to other link piracy sites ($p < 0.05$ and $p < 0.1$, respectively). Conversely, unemployed users divert less to link piracy sites ($p < 0.05$) and log fewer additional minutes on Netflix ($p < 0.05$). These findings may imply that search and switching costs, which fall with education and digital literacy, outweigh higher income when it comes to continuing piracy, whereas income constraints inhibit the move to paid streaming.

6.3. **Implications for Enforcement and Firm Strategy.** For policymakers, the Brazilian case shows that site-level shutdowns can yield measurable legal gains even when only a single domain is targeted, provided that the site is sufficiently dominant and adds enough marginal value/convenience for users compared to alternatives. For legal platforms, the demographic evidence points to the potential value of segment-based pricing or service tiers when enforcement activity is expected. Ad-supported tiering or price discrimination for certain segments of the population may capture price sensitive pirates displaced by enforcement without discounting revenue from existing customers.

6.4. **Future Research.** Our study uses 2015-2016 data; although Brazil's market structure has evolved, site-blocking and domain seizures remain standard tools worldwide, and so the mechanisms remain relevant today. Still, three limitations invite future research. First, income and education are proxied rather than directly observed. Future work with direct socioeconomic data – or experimental variation in SVOD prices – could isolate which margin drives switching. The relatively small size of our panel – just 2,557 Internet users – may have limited the significance of our demographic results.

Second, our study is based in a single market, single-site context. While it adds to several prior studies based in this same context, cross-country replications or multi-site natural experiments could allow greater understanding of why some interventions increase legal update while others fail to do so.

Finally, a field experiment that varies both legal service pricing and enforcement intensity could speak directly to the optimal joint design of anti-piracy policy and platform strategy. Such an experiment could be run by a vertically integrated firm that provides both Internet access (and thus can block sites) and legal services (and thus can vary attributes of those offerings).

References

Adermon, Adrian, and Che-Yuan Liang (2014), "Piracy and Music Sales: The effects of an anti-piracy law", *Journal of Economic Behavior and Organization,* 105; 90-106.

Aguiar L, C. Peukert and J. Claussen (2018), "Catch Me If You Can: Effectiveness and consequences of online copyright enforcement", *Information Systems Research*, 29(3); 525-55.

Brown, J.R. and A. Goolsbee (2002), "Does the Internet Make Markets More Competitive? Evidence from the Life Insurance Industry", *Journal of Political Economy*, 110(3); 481-507.

Brynjolfsson E., A. Dick and M.D. Smith (2010), "A Nearly Perfect Market? Differentiation vs. Price in Consumer Choice", *Quantitative Marketing and Economics*, 8(1); 1-33.

Card, David (1992), "Using Regional Variation in Wages To Measure the Effects of the Federal Minimum Wage", *Industrial and Labour Relations Review*, 46(1); 22-37.

Cameron, A.C. and P. Trivedi (2005), *Microeconometrics: Methods and applications*, Cambridge UK, Cambridge University Press.

Danaher, Brett and Michael D. Smith (2014), "Gone in 60 Seconds: The impact of the Megaupload shutdown on movie sales", *International Journal of Industrial Organization*, 33; 1-8.

Danaher, Brett, Michael D. Smith, Rahul Telang and Siwen Chen (2014), "The Effect of Graduated Response Anti-Piracy Laws on Music Sales: Evidence from an event study in France", *Journal of Industrial Economics*, 62(3); 541-553.

Danaher, Brett, Jonathan Hersh, Michael D Smith, and Rahul Telang (2020), "The Effect of Piracy Website Blocking on Consumer Behavior", *Management Information Systems Quarterly*, 44; 631-59.

Danaher, Brett, Michael D. Smith and Rahul Telang (2017), "Copyright Enforcement in the Digital Age: Empirical evidence and conclusions", *Communications of the Association of Computing Machinery*, 60(2); 68-75.

Festinger, Leon (1957), *A Theory of Cognitive Dissonance (Vol. 2)*, Stanford, Stanford University Press.

Frick, S. J., D. Fletcher and A.C. Smith (2023), "Pirate and Chill: The effect of Netflix on illegal streaming", *Journal of Economic Behavior & Organization*, 209; 334-347.

Ingram, Jason R and Sameer Hinduja (2008), "Neutralizing Music Piracy: An empirical examination", *Deviant Behavior*, 29(4); 334-366.

Mandel, Philipp and Bernd Süssmuth (2012), "Determinants of Digital Piracy: A re-examination of results", *Journal of Economics and Statistics*, 232(4); 394-413.

McKenzie J. (2017), "Graduated Response Policies to Digital Piracy: Do they increase box office revenues of movies?", *Information Economics and Policy*, 38; 1-11.

Nagaraj, A., and I. Reimers (2023), "Digitization and the Market for Physical Works: Evidence from the Google Books Project", *American Economic Journal: Economic Policy*, 15(4); 428-58.

Nishijima, Marislei, Ticiana da Justa and Thais Souza (2020), The Effects of Broadband on the Consumption Film at Theatres in Brazil", *Applied Economics Letters*, 27(8); 637-641.

Peukert C., J. Claussen and T. Kretschmer (2017), "Piracy and Movie Revenues: Evidence from Megaupload", *International Journal of Industrial Organization*, 52; 188-215.

Poort, Joost, Jorna Leenheer, Jeroen van der Ham and Cosmin Dumitru (2014), "Baywatch: Two approaches to measure the effects of blocking access to The Pirate Bay", *Telecommunications Policy*, 38(1); 383-392.

Rajavi, Koushyer, Brett Danaher and Jesse Newby (2024), "Price, Piracy, and Search: Which pirates respond to changes in the legal price?", *MIS Quarterly*, 48(4); 1537-58.

Redondo, Ignacio and Jean-Philippe Charron (2013), "The Payment Dilemma in Movie and Music Downloads: An explanation through cognitive dissonance theory", *Computers in Human Behavior*, 29(5); 2037-2046.

Reis F, de Matos M.G. and P. Ferreira (2024), "Controlling Digital Piracy Via Domain Name System Blocks: A natural experiment", *Journal of Economics, Behavior, and Organization*, 218; 89-103.

Riekkinen, Janne (2016), "Dissonance and Neutralization of Subscription Streaming Era Digital Music Piracy: An initial exploration", in *PACIS 2016: Proceedings of the 20th Pacific Asia Conference on Information Systems*, ISBN 9789860491029, Association for Information Systems.

Sykes, Gresham M. and David Matza (1957), "Techniques of Neutralization: A theory of delinquency", *American Sociological Review*, 22(6); 664-670.

Appendices

Appendix A – List of Included Sites in 2015 Analysis

In order to determine the list of piracy sites to track, we first compiled a list of all known piracy sites from a combination of illegal site lists, our panel tracking company's piracy category, and a thorough search through piracy channels and bulletin boards. We then had our panel tracking company provide data for the top thirty two sites, the number of sites that captured 80% of total piracy visits. The following sites are those for which we observed visits in our data.

Host Piracy

4shared.com

mega.co.nz

uploaded.net

zippyshare.com

openload.co

sendspace.com

theuniversedownload.com

P2P Piracy

torrentdosfilmes.com

torrentfilmeshd.org

thepiratefilmeshd.com

thepiratefilmes.com

piratefilmestorrent.com

thepiratebrazil.org

thepiratebay.se

teutorrent.com

Link Piracy

filmesonlinegratis.net

filmesonlinehd1.com

megafilmesonline.net

ilovefilmesonline.com

armagedomfilmes.biz

filmesonlinex.net

seriesonlinehd.org

filmesserieshd.com

legendas.tv

filmeseseriesonline.net

supercineonline.tv

megaboxfilmesonline.com

filmesmegahd.net

sobaixar.com

hdfilmesonlinegratis.net

megafilmesonlinehd.com

megafilmeshd20.org

Legal Subscription Sites

netflix.com

Cable Subscription

netcombo.com.br

globosatplay.globo.com/telecine

www.hbogo.com.br

Ad Supported and EST Sites

foxplaybrasil.com.br

crackle.com.br

youtube.com/channel/uclgrkhtl3_himcamdlfde4g

play.google.com/store/movies

www.vivoplay.com.br

Appendix B – Selection of Piracy Sites to Include in Study

An important question is how the sites included in each bucket were selected and whether that encompass the bulk of piracy sites visited by Brazilians. In order to determine which sites to track in each bucket, we adopted the following process:

(1) First, we simply attempted to find piracy sites using Google and obvious searches such as "pirate movies" or "watch movies free online" while connected to a Brazilian VPN. This primarily returned pirate sites that either exclusively provided access to copyright-infringing files in Portuguese or with Portuguese subtitles, though it

also included sites that provided some content in other languages but a substantial number of Portuguese options.

(2) We supplemented the list from step #1 by speaking directly with representatives of the Motion Picture Association in Brazil, whose job it is to monitor where Brazilians go to pirate content.

(3) We provided the full list from step #1 and step #2 to Netquest, who supplemented it with any sites to which they had observed visits in their data that they had classified as a piracy site. Steps 1, 2, and 3 yielded a list of over 200 piracy sites.

(4) Netquest then determined which of the piracy sites from this list had any visits at all during the time period studied. This reduced the list significantly because because piracy is concentrated on a particular set of sites at any given time, and many of the unique website addresses that exist are sparsely used mirrors of some of these main piracy sites.

(5) We tasked a student who spoke Portuguese with visiting each of these sites using a laptop and Brazilian VPN which we provided. By visiting each site, she was able to validate that it was indeed a piracy site (and drop it if not) and then determine whether it was a p2p site, host site, or link/streaming site.

The resulting list of piracy sites, found in Appendix A, are assumed to comprise the majority of Brazilian piracy. It is possible that some sites could be missing, though it is unlikely that such sites are used extensively as they likely would have been flagged in steps 1, 2, or 3 if so. If some piracy is missing from our observation, the effect of this on our estimates might be differenced out by our panel estimation approaches.

Appendix C – Additional tables

Table C1: Robustness of Impact of MegafilmesHD Block on Visits to Legal and Illegal Websites, Using Panel OLS Model and Ln(minutes + 1 as the Dependent)

Site Type	**Host Piracy**	**Peer-to-Peer**	**Link Piracy**	**Paid Subscription**
Dependent Variable	*Visits*	*Visits*	*Visits*	*Visits*
Post	-0.0484***	0.0675***	0.160***	0.0858***
	(0.00937)	(0.00698)	(0.0153)	(0.0131)
Pre-Period Visits to Megafilmes x Post	0.0000296	0.0000912	0.00655***	0.00168*
	(0.000273)	(0.000179)	(0.00127)	(0.000675)
Constant	0.469***	0.125***	0.465***	0.389***
	(0.00460)	(0.00341)	(0.00703)	(0.00653)
N	15342	15342	15342	15342
Individuals	2557	2557	2557	2557
Within-R2	0.003	0.013	0.067	0.012
Between-R2	0.005	0.002	0.158	0.017
Month FEs	Y	Y	Y	Y
Individual FEs	Y	Y	Y	Y
Estimator	Panel OLS	Panel OLS	Panel OLS	Panel OLS

Standard errors in parentheses, clustered at individual level.
*** $p < 0.001$ ** $p < 0.01$ * $p < 0.05$ + $p < 0.1$

Table C2: Robustness of Impact of MegafilmesHD Block on Minutes at Legal and Illegal Websites, Using Negative Binomial Fixed Effects Model

Site Type	**Host Piracy**	**Peer-to-Peer**	**Link Piracy**	**Paid Subscription**
Dependent Variable	*Minutes*	*Minutes*	*Minutes*	*Minutes*
Post	-0.136***	0.661***	0.428***	0.321***
	(0.0303)	(0.0538)	(0.0320)	(0.0365)
Treat Intensity: Pre-Period Visits to Megafilmes	0.00127+	0.000300	0.00165**	-0.00102
	(0.000735)	(0.00142)	(0.000535)	(0.000688)
Pre-Period Visits to Megafilmes x Post	0.000391	-0.0000848	0.00295***	0.00153+
	(0.000744)	(0.00141)	(0.000557)	(0.000804)
Constant	-1.177***	-1.555***	-1.934***	-1.983***
	(0.0285)	(0.0530)	(0.0289)	(0.0319)
N	10434	4212	9408	7344
Individuals	1739	702	1568	1224
Log-Likelihood	-12714.92	-4094.69	-18439.93	-15479.84
Month FEs	Y	Y	Y	Y
Individual FEs	Y	Y	Y	Y
Estimator	Panel OLS	Panel OLS	Panel OLS	Panel OLS

Standard errors in parentheses.
*** $p < 0.001$ ** $p < 0.01$ * $p < 0.05$ + $p < 0.1$

Table C3: Moderating Effect of Demographic Group on Link Piracy Visits

Dependent Variable	*Visits*	*Visits*	*Visits*	*Visits*	*Visits*	*Visits*	*Visits*	*Visits*
Female * Post * Treatment Intensity	-0.00627***							
	(0.00116)							
Age < 35 * Post * Treatment Intensity		0.0000376						
		(0.00117)						
Rio or Sao Paulo * Post * Treatment Intensity			0.00217+					
			(0.00122)					
Professional * Post * Treatment Intensity				0.00299*				
				(0.00138)				
Number of Children * Post * Treatment Intensity					0.000628			
					(0.000619)			
Unemployed * Post * Treatment Intensity						-0.00328**		
						(0.00112)		
Student * Post * Treatment Intensity							0.00174	
							(0.00197)	
Main Earner * Post * Treatment Intensity								0.00110
								(0.00115)
N	9408	9408	9408	9408	9408	9408	9408	9408
Individuals	1568	1568	1568	1568	1568	1568	1568	1568
Month FEs	Y	Y	Y	Y	Y	Y	Y	Y
Individual FEs	Y	Y	Y	Y	Y	Y	Y	Y
Log-Likelihood	-13388.41	-13400.56	-13397.45	-13398.72	-13398.61	-13393.08	-13401.06	-13401.84

Standard errors in parentheses. Other coefficients suppressed and available upon request.
*** p < 0.001 ** p < 0.01 * p < 0.05 + p < 0.1

Table C4: Moderating Effect of Demographic Group on Link Piracy Minutes

Dependent Variable	*Log of Minutes*	*Log of Minutes*	*Log of Minutes*	*Log of Minutes*	*Log of Minutes*	*Log of Minutes*	*Log of Minutes*	*Log of Minutes*
Female * Post * Treatment Intensity	-0.00919*							
	(0.00382)							
Age < 35 * Post * Treatment Intensity		-0.00340						
		(0.00535)						
Rio or Sao Paulo * Post * Treatment Intensity			0.00415					
			(0.00362)					
Professional * Post * Treatment Intensity				0.00486				
				(0.00408)				
Number of Children * Post * Treatment Intensity					0.00152			
					(0.00170)			
Unemployed * Post * Treatment Intensity						-0.00907**		
						(0.00319)		
Student * Post * Treatment Intensity							0.00275	
							(0.00458)	
Main Earner * Post * Treatment Intensity								0.00162
								(0.00410)
N	15342	15342	15342	15342	15342	15342	15342	15342
Individuals	2557	2557	2557	2557	2557	2557	2557	2557
Month FEs	Y	Y	Y	Y	Y	Y	Y	Y
Individual FEs	Y	Y	Y	Y	Y	Y	Y	Y
Within-R2	0.053	0.050	0.050	0.050	0.050	0.054	0.050	0.049
Between-R2	0.142	0.165	0.159	0.158	0.159	0.162	0.155	0.153

Standard errors in parentheses. Other coefficients suppressed and available upon request.
*** p < 0.001 ** p < 0.01 * p < 0.05 + p < 0.1

Table C5: Moderating Effect of Demographic Group on Subscription Visits

Dependent Variable	*Visits*	*Visits*	*Visits*	*Visits*	*Visits*	*Visits*	*Visits*	*Visits*
Female * Post * Treatment Intensity	0.00332							
	(0.00211)							
Age < 35 * Post * Treatment Intensity		-0.00200						
		(0.00246)						
Rio or Sao Paulo * Post * Treatment Intensity			0.00364+					
			(0.00215)					
Professional * Post * Treatment Intensity				0.00420+				
				(0.00231)				
Number of Children * Post * Treatment Intensity					-0.000130			
					(0.000929)			
Unemployed * Post * Treatment Intensity						-0.00174		
						(0.00184)		
Student * Post * Treatment Intensity							-0.00492*	
							(0.00234)	
Main Earner * Post * Treatment Intensity								0.000987
								(0.00170)
N	7344	7344	7344	7344	7344	7344	7344	7344
Individuals	1224	1224	1224	1224	1224	1224	1224	1224
Month FEs	Y	Y	Y	Y	Y	Y	Y	Y
Individual FEs	Y	Y	Y	Y	Y	Y	Y	Y
Log-Likelihood	-10109.71	-10112.25	-10100.36	-10109.89	-10108.68	-10106.49	-10109.15	-10109.83

Standard errors in parentheses. Other coefficients suppressed and available upon request.
*** p < 0.001 ** p < 0.01 * p < 0.05 + p < 0.1

Table C6: Moderating Effect of Demographic Group on Subscription Minutes

Dependent Variable	*Log of Minutes*	*Log of Minutes*	*Log of Minutes*	*Log of Minutes*	*Log of Minutes*	*Log of Minutes*	*Log of Minutes*	*Log of Minutes*
Female * Post * Treatment Intensity	0.00230							
	(0.00210)							
Age < 35 * Post * Treatment Intensity		0.000437						
		(0.00200)						
Rio or Sao Paulo * Post * Treatment Intensity			0.00260					
			(0.00244)					
Professional * Post * Treatment Intensity				0.00345				
				(0.00336)				
Number of Children * Post * Treatment Intensity					0.000467			
					(0.00151)			
Unemployed * Post * Treatment Intensity						-0.00387*		
						(0.00191)		
Student * Post * Treatment Intensity							-0.00281	
							(0.00402)	
Main Earner * Post * Treatment Intensity								-0.00213
								(0.00248)
N	15342	15342	15342	15342	15342	15342	15342	15342
Individuals	2557	2557	2557	2557	2557	2557	2557	2557
Month FEs	Y	Y	Y	Y	Y	Y	Y	Y
Individual FEs	Y	Y	Y	Y	Y	Y	Y	Y
Within-R2	0.012	0.012	0.013	0.012	0.012	0.013	0.013	0.012
Between-R2	0.019	0.027	0.010	0.012	0.022	0.017	0.026	0.021

Standard errors in parentheses. Other coefficients suppressed and available upon request.
*** p < 0.001 ** p < 0.01 * p < 0.05 + p < 0.1

Brett Danaher and Jonathan Hersh; Argyros College of Business and Economics, Chapman University, Orange, CA 90041. danaher@chapman.edu, hersh@chapman.edu. Michael D Smith; Heinz College, Carnegie Mellon University, Pittsburgh, PA 15213. mds@cmu.edu., This research was conducted as part of Carnegie Mellon University's Initiative for Digital Entertainment Analytics (IDEA), which receives unrestricted (gift) funding from the Motion Picture Association of America. The authors thank Jesse Newby and Runshan Fu for excellent research assistance. All findings and errors are entirely our own.