The Impact of Video Piracy on Content Producers and Distributors*

Zachary Nolan† Jonathan W. Williams‡ Haoran Zhang§

September 28, 2022

Abstract

Recent advances in digital media streaming technology improve access to content, but can also facilitate piracy, creating trade-offs for content producers and multiple-system operators (MSOs). We use novel household-level data describing internet and TV usage together with the timing of Kodi software adoption to quantify damages from media piracy. We find that adoption does not decrease viewership of paid over-the-top video subscriptions like Netflix, and that many other applications see increased engagement. TV subscriptions decrease and internet-tier upgrades increase, resulting in a 1% reduction in household payments to MSOs. These behavioral changes harm content producers that rely on the MSO for distribution via reduced licensing and advertising revenues, and result in a decrease in profits for MSOs with TV margins in excess of 30%. Collectively, these results support a series of lawsuits claiming damages to selected MSOs and content producers.

Keywords: Intellectual Property, Piracy, Digitization, Telecommunications

JEL Codes: L11, L13, L96.

*We thank the National Science Foundation (Grant SES-1324717), the NET Institute, and Cable Television Laboratories, Inc., and its member organizations, for their support of this work. We are grateful for the generosity of the North American ISPs that provided the data used in this paper. All remaining errors are our own.

†Department of Business Administration, University of Delaware, znolan@udel.edu

‡Department of Economics, University of North Carolina at Chapel Hill, jonwms@unc.edu.

§Department of Economics, University of North Carolina at Chapel Hill, hz124@unc.edu.

1 Introduction

Intellectual property (IP) protections play a vital role in maintaining incentives to innovate. These protections include trademarks, copyrights, and patents, each of which grant a degree of market power to innovators to encourage the development of new content and technology. However, in some markets, IP protection enforcement can be difficult, leading to a deterioration of its intended effects. These enforcement challenges are particularly acute in the rapidly-growing markets for digital goods, in which replication and distribution are both low-cost and difficult to observe.

The combined revenue generated by digital media markets (including gaming, video, music, e-books, etc.) worldwide exceeds \$330 billion annually, a figure expected to continue growing in excess of 10% per year as broadband access increases and firms reach new customers and markets. One of the largest segments of this market, accounting for nearly two-thirds of all residential internet traffic, is over-the-top (OTT) video subscription services like Netflix, HBO Max, and Sling TV.[1] Recent technological developments in this industry have made unlicensed access to subscription and live video content simple, inexpensive, and difficult to detect, potentially eroding protections granted to content producers. Specifically, Kodi streaming software, which facilitates both legal and unlicensed access to content from OTT subscription services, became readily available on streaming devices in the late-2010s. The emergence of Kodi also introduces a trade-off for multiple-service operators (MSOs): although demand for paid video services may decrease with the availability of unlicensed alternatives, the bandwidth requirements of piracy methods may increase the demand for high-quality internet access. The potential for redistribution of surplus among content providers, MSOs, and consumers has important implications for the incentives that govern content creation and broadband network investment. In this paper, we use novel detailed panel data on households' internet and video usage, and adoption timing of Kodi-ready streaming hardware, to quantify the impact of piracy on content producers and MSOs.

In the late 2010s, open-source "Kodi" software was recognized as a means to overcome

[1]See https://www.statista.com/outlook/dmo/digital-media/worldwide#revenue

barriers to media piracy even for technologically unsophisticated households.[2] Soon after, entrepreneurs began selling streaming media hardware pre-loaded with Kodi software at retailers like Amazon, which facilitated illegal access to live and on-demand video programming. These devices offered free or inexpensive access to programming after the fixed cost to obtain them, prompting a surge in demand and numerous lawsuits from content producers (including Amazon, Disney, Netflix, NBC Universal, and others) seeking damages for copyright infringement.[3]

In addition to the challenges of quantifying damages, IP protection enforcement for digital media is difficult. In particular, internet-access providers, including MSOs that sell both live TV and internet-access services, may not have the ability or incentive to mitigate piracy. On one hand, Kodi boxes offer free (or very inexpensive) access to live TV programming that may be superior (i.e., thousands of channels from across the globe) to the MSO's TV service. On the other hand, a household must have access to a high-speed internet connection to utilize these substitutes, making high-quality internet access more valuable. Even if the former harm outweighs the latter benefit, it is not clear that MSOs could easily mitigate piracy of copyrighted digital content. Specifically, the technology (i.e., BitTorrent) that turns standard streaming hardware into a platform for piracy was an original catalyst for implementation of strong Net Neutrality standards requiring the equal treatment of internet traffic. In 2008, when Comcast blocked BitTorrent from its network due to concerns over harm from network congestion (and its use in piracy), the Federal Communications Commission (FCC) ruled that this was a violation of Net Neutrality principles.[4] Also, the Digital Millennium Copyright Act (DMCA) prevents MSOs from directly benefiting from copyright infringements, ruling out application-specific fees to extract a portion of the surplus associated with Kodi adoption. Thus, MSOs could face regulatory scrutiny on multiple fronts for impeding traffic associated with these activities.

The high-frequency panel data at the core of our empirical analysis help overcome

[2]Before Kodi, the most common method for media piracy was BitTorrent, a protocol enabling users to send, receive, and locally store large files in a decentralized manner.

[3]See: https://www.forbes.com/sites/ianmorris/2018/04/29/netflix-and-amazon-join-the-battle-against-kodi-pirates/?sh=1421080e213a

[4]https://www.cnet.com/news/fcc-formally-rules-comcasts-throttling-of-bittorrent-was-illegal/

challenges with quantifying the damages to digital media content providers and measuring the incentives of MSOs regarding piracy. Specifically, for about 10,000 households, we observe if and when each household adopts Kodi technology, engagement with popular OTT subscription services, and subscriptions and engagement with the MSO's live TV and internet services. Our ability to observe adoption relies on deep-packet inspection (DPI) software on the MSO's network that can detect traffic associated with specific applications and devices, including Kodi. At an hourly frequency, we also observe internet usage for eleven broad categories including gaming, web browsing, and real-time communication. For all traffic within the largest of these categories, real-time entertainment (RTE), which accounts for nearly two-thirds of all traffic, we observe event-level usage information. Each record in these more detailed data includes a unique household identifier, identity of the application (e.g, Netflix), device utilized (e.g., Roku), and total bytes and duration (e.g., 1 gigabyte used over 45 minutes). In addition to this DPI internet usage information, we observe set-top box (STB) log files describing TV viewership on the MSO's live TV service.

Directly observing the household-specific timing of Kodi adoption, along with subsequent changes in engagement and subscriptions, offers an opportunity to quantify both harm to providers of digital media and the MSO's incentives to prevent or extract surplus associated with piracy. Our household-level panel begins before pre-loaded Kodi devices became widely available, so for most households we observe a period of several months both before and after adoption. However, adoption is a choice, and those 9.5% of households that adopt exhibit behaviors different from other households. Kodi-adopting households generate 11.38 gigabytes of internet traffic per day, nearly 65% more data than the 6.91 daily gigabytes generated by other households. Engagement with some RTE services is also substantially higher for Kodi households: Twitch (371%), Hulu Live (394%), and DirecTV Now (169%). To address these challenges and identify the effects of Kodi adoption, we utilize the synthetic difference-in-differences (SDID) approach of Arkhangelsky et al. (2021).[5] In our application, the SDID method provides a household-

[5]See Abadie et al. (2010) and Cunningham and Shah (2018) for early applications of synthetic control methods.

specific expectation of the usage and subscription behaviors that would have been realized in the absence of Kodi adoption using a weighted average of other households with similar behaviors. Combining this estimate of counterfactual behaviors with the realized behaviors allows us to identify the behavioral effect of adoption on a household. We consider a variety of engagement and subscription outcomes to quantify the impact of Kodi adoption on content producers and MSOs.

First, we examine the effect of Kodi adoption on MSO subscriptions and profitability. We find that Kodi adopters' expenditure on MSO services drops by about 1%. This is the net effect of video expenditure (e.g., "cutting the cord"), a decrease of 3.1%, and internet service expenditure (e.g., tier upgrades), an increase of 0.9%. Consistent with an increase in demand for internet services, a household's total usage increases by 2.89 gigabytes per day (26%) following Kodi adoption. This is primarily driven by increases in RTE and bulk transfers (e.g., encrypted traffic) of 1.72 and 0.62 gigabytes, respectively. Precipitous increases in network traffic could harm MSO profitability by accelerating the schedule of fixed-cost network investments (e.g., node splits).

Next, we look at engagement with specific sources of traffic within the RTE category. Consistent with the large increase in RTE traffic following Kodi adoption, we find traffic associated with subscription video on demand (SVOD) services increases by 0.52 gigabytes per day, the equivalent of up to 30 minutes of high-definition (1080p) video content on a typical service. Netflix, YouTube, live TV (e.g., Sling TV), and social-media applications see positive and significant increases in usage following Kodi adoption. We find no statistically significant effect on the intensity of engagement with the MSO's TV service overall or for any genre of channels. Thus, Kodi adoption led to an increase in legal engagement with most sources of OTT content, and the intensity of engagement with the MSO's TV service was largely unchanged.

Together, our findings show that adoption of pre-loaded Kodi boxes by a household increases engagement with most sources of content. These findings are consistent with Kodi making access to various OTT video sources easier, and inconsistent with many allegations of harm to online content providers. However, content producers that rely on the MSO for distribution do suffer harm from lost advertising and licensing revenues due to the reduction in subscriptions to the MSO's TV service. As for harm to the MSO, the observed decrease in revenue corresponds to a decrease in profits only if the margin associated with lost TV revenue is large enough to offset the margin associated with increased internet revenue. If one assumes that internet service has zero marginal cost, TV margins must be greater than 30% for Kodi adoption to result in a decrease in MSO profits. This threshold moves down if accommodation of Kodi traffic requires additional network investment. For smaller MSOs with less bargaining power to reduce TV content licensing fees, Kodi adoption may actually increase profits. For large MSOs that are vertically integrated with content providers (e.g., Comcast and NBC Universal), 30% margins are more plausible and therefore justify the litigation alleging harm.[6]

Given the legal and regulatory limits on MSOs' ability to block or price Kodi traffic, government and private entities also took steps to limit distribution of Kodi boxes while litigation proceeded. At the peak of Kodi adoption, some governments including the EU made the sale of pre-loaded Kodi hardware illegal, leading to a number of arrests and fines.[7] In cooperation with these efforts, Google eliminated auto-completion for terms related to Kodi and altered their search algorithms to de-prioritize such material.[8] These coordinated efforts ultimately were successful in nearly eliminating the market for pre-loaded Kodi boxes, an outcome which benefits MSOs with relatively large margins on TV service, and content producers that rely on MSOs for distribution. However, in the short run, it harms OTT content providers that realize increased legal engagement following Kodi adoption. Given the dissolution of the market, identifying longer-run changes in engagement is no longer possible. However, over our 16-month panel of data, we find no evidence to suggest the effects of Kodi change with the time since adoption.

Our research complements a rich literature on intellectual property and piracy, particularly for digital goods. The theoretical effect of file-sharing technologies on copyright

[6]One such suit alleging harm was recently settled: https://www.theverge.com/2022/3/1/22956219/kodi-tvaddons-creator-fined-19-million-copyright-infringement-piracy

[7]https://www.theverge.com/2017/4/26/15433342/eu-court-of-justice-filmspeler-kodi-piracy-box-ruling

[8]https://www.theverge.com/2018/3/29/17176894/google-removes-kodi-search-autocomplete-anti-piracy

holders is ambiguous because technologies that facilitate piracy may encourage legal sales through awareness and other channels (Takeyama, 1997; Bakos and Brynjolfsson, 2000; Varian, 2000; Shapiro et al., 1998). Oberholzer-Gee and Strumpf (2007) and Oberholzer-Gee and Strumpf (2016) find that Napster had no effect on music sales, and Waldfogel (2012) finds no change in quality of music.[9] Danaher and Waldfogel (2012) and Leung (2015) find losses associated with piracy for movie box office and music sales, respectively. Our findings show that Kodi adoption increased subscriptions and engagement with many sources of OTT content, but likely harmed MSOs and content producers that rely on MSOs for distribution.

We also contribute to a growing empirical literature focused on MSO incentives regarding the treatment of new technologies on their networks. Numerous studies measure the determinants of the value derived from internet access broadband (Prince and Greenstein, 2017; Goetz, 2019; Tudon, 2021; Goolsbee and Klenow, 2006; Dutz et al., 2012; Rosston et al., 2013; Greenstein and McDevitt, 2011; Edell and Varaiya, 1999; Varian, 2002; Hitt and Tambe, 2007). Our analysis shows that innovations like Kodi that increase demand for broadband can harm the MSO's TV service and overall revenue. McManus et al. (2022) show that MSOs will embrace innovations (OTT video in their setting) so long as they can capture some of the increase in surplus associated with internet access. In our setting, where DMCA and regulatory uncertainty over net neutrality limit the strategies available to MSOs, litigation became the obvious solution to limit adoption of the innovation. This contributes more empirical evidence related to the "net neutrality" debate over MSO's incentives regarding blocking, pricing, or throttling different sources of traffic.[10] Our high-frequency internet usage data are similar to those used by Nevo et al. (2016), Malone et al. (2021), and Malone et al. (2014), but we observe application-level data (e.g., Netflix) in addition to engagement with the MSO's TV service.

[9]Other important early contributions to this literature include Peitz and Waelbroeck (2004), Rob and Waldfogel (2006), Zentner (2006), and Rob and Waldfogel (2007).

[10]Lee and Wu (2009) and Greenstein et al. (2016) provide excellent discussions of this literature.

2 Data

Our data describe the characteristics and behaviors of 10,337 households, all of whom take up service from a North American MSO.[11] For each household, we observe internet and TV usage data and billing records over a sixteen-month period spanning 2017-2018. In this section we describe the four data sources that comprise our sample, document evidence of media piracy via Kodi software, and describe behavioral changes that occur when a household adopts piracy technology.

2.1 Data sources

The first data source is a collection of usage reports from in-home internet connectivity hardware, which contains an hourly aggregation of the quantity of internet traffic generated by each household. These reports capture both upload and download traffic, measured in bytes. The hourly traffic totals are also decomposed into categories including web browsing, email, gaming, and real-time entertainment (RTE; applications and protocols that provide "on-demand" entertainment that is consumed as it arrives, e.g., Netflix, YouTube, etc.). A list of categories with example applications and protocols is provided in Table 1.

This aggregate information on internet usage is supplemented by high-frequency detail on all activity within the RTE category, which accounts for approximately 63% of overall traffic in the sample. This second data source is at the event level, and includes the time stamp, duration, size, and content provider associated with all consumption events within this category. Most applications and content providers in the raw data are identified by a provider name (e.g., Netflix), but some include only an IP address. We use a DNS lookup tool[12] to identify the content provider associated with each IP address. After filling in the unknown content providers, we can identify the source of 99.99% of traffic within the RTE category.

The third data source is set-top box data describing the channel and viewing duration

[11] The demographics of households in the sample market are approximately representative of the U.S. population.

[12] https://www.home.neustar/resources/tools/ip-geolocation-lookup-tool

Table 1: Internet Traffic Categories

Category	Description
Bulk Transfer	Large file transfers (FTP, SFTP)
Cloud	Cloud storage (Dropbox, Google Drive)
Email	Service-provider and webmail e-mail services (Gmail, SMTP, POP3)
Gaming	Console and PC gaming (PlayStation, XBox)
Peer-to-Peer	File-sharing applications (BitTorrent)
Real-Time Communication (RTC)	Interactive video and voice communications (Skype, Zoom)
Real-Time Entertainment (RTE)	Applications involving “on-demand” entertainment that is consumed as it arrives (Netflix, Youtube, RTSP, Flash)
Social Media	Social networking websites (Facebook, Twitter)
Tunnel	Encrypted channels used for VPN and secure web transactions (SSL, SSH)
Web Browsing	Individual websites (HTTP)
Miscellaneous	Uncategorized traffic

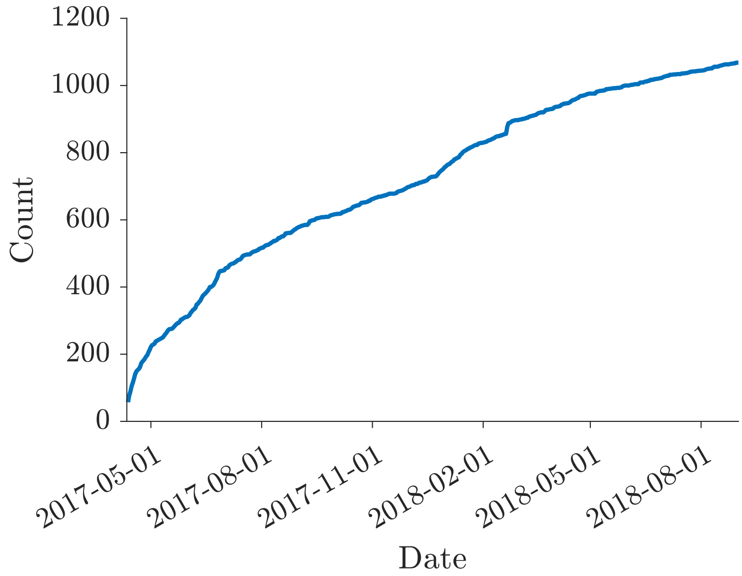
Notes: List of categories observed in the hourly internet traffic reports with descriptions and example applications or protocols.

of TV tuning events at a one-minute frequency. This data source is available for the 67% of households that subscribe to a TV plan in addition to internet access.

The final data source provides billing information and allows us to link together the three types of usage data via a stable subscriber identifier. For each subscriber identifier, we have a record of which services were chosen in addition to payments made to the ISP for these services. The services available include TV plans (e.g., Basic TV, Expanded TV, HBO, etc.), internet service tiers (differentiated by download speed), and home phone service. Nearly all households we observe take up internet service, and 67% take up TV service.

To combine the three usage data sources, each of which comes at a different level of observation, we aggregate to the household-day level of observation. The consumption panels we use in the analysis contain each household’s daily internet consumption by category, RTE consumption by content provider, and TV consumption by network.

Figure 1: Number of Kodi Users



Notes: Cumulative number of active Kodi users. Sample time frame is April 11, 2017 to August 31, 2018.

2.2 Identifying media piracy

We identify households that engage with media piracy software from the RTE data, which include a record of engagement with Kodi software. Media piracy is not the sole-use case of Kodi software, but the software facilitates access to unlicensed content via third-party add-ons. Kodi has become closely associated with piracy due to the practice of bundling its software with media streaming hardware and add-on software pre-configured to access unlicensed content, so-called "fully-loaded" Kodi boxes.

When a subscriber initiates a video stream within the Kodi application, a new data flow originates from a specific IP address that hosts unlicensed content. The Kodi traffic we observe comes from system refreshes and updates to the Kodi software and/or its add-ons.[13] This means our measure of piracy engagement is imperfect: although we have a good signal of the extensive margin (adoption) or the technology, the exact volume of traffic passed through Kodi software is not observable. A household in our sample is labeled a Kodi *adopter* if we ever observe traffic attributed to the Kodi application. We

[13]These updates are frequent. Kodi software developers released a new version of the application in early 2017, with monthly updates for the rest of the year. Also, each third-party add-on that facilitates access to unlicensed content is a separate entity, managed by its own developer team which publishes its own software updates.

also use *adoption date* to refer to the date on which the application was first used.

During the sample, we observe about 1,000 households utilize Kodi software. Figure 1 depicts this adoption over time. For a period of approximately 100 days at the beginning of the sample, we observe no households engage with Kodi (omitted from the figure), but use of the application grows quickly beginning in 2017. The overall penetration rate, approximately 9.5% of our sample, is in line with an industry report from Sandvine which estimated that 8.8% of North American households had a Kodi box during our sample period. Although we cannot be certain whether each individual household utilizes Kodi for piracy, the same report determines that over two-thirds of households with Kodi devices also have add-ons configured to access unlicensed content (Sandvine, 2017).

2.3 Descriptive statistics of usage

Internet and TV usage during the sample period is characterized by significant heterogeneity and growth during the panel. Table 2 provides summary statistics on the distribution of internet and TV usage across households. The average household in the sample generated 7.34 gigabytes per day of total internet usage. The distribution of internet usage is highly skewed: the standard deviation is 13.18, the 25th percentile is 0.85, and the 75th percentile is 9.18 gigabytes per day. Heavy internet use is driven by the use of streaming video entertainment, with RTE usage generating 63% of overall usage. 67% of the households in the sample take up a TV subscription in addition to internet access. Engagement with TV is also highly heterogeneous, with the average TV household viewing 4.33 hours per day (standard deviation 6.14).

Table 2: Internet and TV Usage

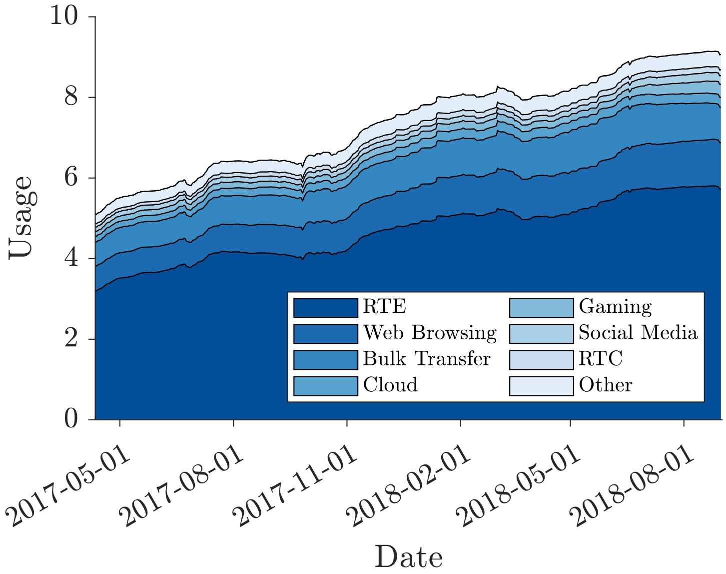
	Mean	SD	p25	p50	p75	Count
Internet Usage						
All households	7.34	13.18	0.85	3.00	9.18	10,337
Non-Kodi adopters	6.91	12.67	0.79	2.74	8.53	9,357
Kodi adopters	11.38	16.67	2.00	6.53	15.13	980
RTE Usage						
All households	4.66	8.92	0.15	1.23	5.80	10,337
Non-Kodi adopters	4.37	8.57	0.13	1.07	5.33	9,357
Kodi adopters	7.41	11.29	0.62	3.61	10.13	980
TV Usage						
All households	4.33	6.14	0	1.92	6.63	6,922
Non-Kodi adopters	4.25	6.10	0	1.85	6.48	6,420
Kodi adopters	5.19	6.50	0	2.9	8.08	502

Notes: This table summarizes household-level average daily internet usage, real-time entertainment (RTE) usage, and TV usage. Internet usage is measured in gigabytes and TV usage is measured in hours. Statistics from each usage distribution are provided for all households, households that utilize Kodi, and households that do not utilize Kodi.

Internet usage is also characterized by significant growth during the sample period. Figure 2 depicts the growth in total usage over the course of the sample (height of the boundary between shaded and unshaded regions) and the breakdown of total usage into categories (height of individual shaded bands). Internet engagement grows significantly, from a household daily average of 5 gigabytes per day during the first month to nearly 9 gigabytes per day during the last month, an annual growth rate of approximately 50%.

Although traffic as a whole grows rapidly, the composition of traffic is relatively stable during the sample, with RTE making up the majority of traffic, followed by web browsing and bulk transfer (large data transfers using FTP or its derivatives). Levels of each traffic category are documented in Table 3, and more information on this grouping is provided in the data appendix.

Figure 2: Internet Usage Growth and Composition



Notes: 30-day rolling average of internet usage (measured in gigabytes) by traffic category. Band heights correspond to the volume of traffic within the corresponding category. The three smallest categories are combined with the Miscellaneous category and labeled “Other”.

Table 3: Internet Usage by Category

	All HHs	Non-Kodi	Kodi	Difference (%)
Total	7.341	6.907	11.378	64.74
RTE	4.663	4.368	7.405	69.54
Web Browsing	0.867	0.827	1.235	49.25
Bulk Transfer	0.837	0.781	1.354	73.30
Cloud	0.210	0.205	0.259	26.59
Miscellaneous	0.201	0.197	0.237	20.26
RTC	0.119	0.110	0.204	86.29
Gaming	0.176	0.163	0.297	82.46
Social Media	0.139	0.135	0.180	33.87
Peer-to-Peer	0.061	0.056	0.112	100.37
Tunnel	0.046	0.044	0.067	52.44
Email	0.023	0.022	0.028	25.19

Average daily usage by internet traffic category for all households, households that do not adopt Kodi, and households that adopt Kodi. Difference (%) is the percent difference between Kodi and Non-Kodi households. Usage is measured in gigabytes.

Next, we describe the set of individually observable applications within the real-time entertainment category. Table 4 provides summary statistics for the top 30 applications by total usage volume. Approximately 40% of traffic in the real-time entertainment category is attributable to engagement with Netflix, and another 19% is due to YouTube. Three of the five most-used applications are the largest subscription video on-demand services—Netflix, Amazon Video, Hulu—which together account for 52% of all RTE traffic. These applications are followed by Sling TV, an online live TV programming distributor offering a close substitute to the ISP's TV product. Other similar applications including DirecTV/AT&T TV Now, PlayStation Vue, and Hulu Live TV are also observable. These high-volume applications exhibit large unconditional usage averages with low overall penetration. The remaining applications in the RTE category include social media (Facebook, Instagram, TikTok, Twitter), music streaming (iTunes, Pandora, musical.ly), individual content providers (HBO, ESPN, Fox, MLB), and some unsorted traffic or traffic attributable to a CDN (HTTP Live Streaming, CDN, Akamai). The final column in Table 4 includes the number of households that ever engage with the application. In the case of subscription services like Netflix, which 89% of households use at least once, this is likely an overestimate of the true penetration rate of subscriptions due to the availability of free trials and other promotions. Many free applications like YouTube and Facebook have nearly full penetration within the sample. The appendix contains a table similar to Table 4 with applications ranked by penetration rate instead of volume.

Table 4: Usage of Top 30 Real-Time Entertainment Applications

	All HHs	Non-Kodi	Kodi	Difference (%)	Count
Netflix	1.95	1.858	2.748	47.96	8,808
YouTube	0.851	0.79	1.387	75.54	10,103
Amazon Prime Video	0.435	0.413	0.624	51.12	6,883
HTTP Live Streaming	0.237	0.221	0.372	68.1	10,034
Hulu	0.166	0.158	0.232	46.73	2,891
Facebook	0.131	0.127	0.247	95.03	10,016
Sling TV	0.104	0.102	0.118	15.2	934
Twitch	0.074	0.065	0.162	149.96	6,164
HBO	0.062	0.059	0.094	59.51	2,028
Apple	0.061	0.06	0.073	21.97	7,320
CDN	0.059	0.056	0.086	53.1	9,718
iTunes	0.056	0.056	0.056	-1.03	8,616
PlayStation Vue	0.047	0.045	0.068	50.81	205
Pandora	0.041	0.039	0.061	55.37	6,576
musical.ly	0.04	0.036	0.075	107.68	2,497
Akamai	0.039	0.036	0.061	67.15	9,764
DirecTV Now	0.038	0.034	0.088	158.66	326
Vudu	0.035	0.035	0.033	-5.63	861
ESPN	0.03	0.029	0.044	51.02	6,096
Instagram	0.02	0.019	0.083	341.2	2,849
MLB	0.018	0.016	0.032	99.53	2,191
Twitter	0.017	0.017	0.024	43.68	9,272
Amazon	0.016	0.016	0.019	21.2	9,738
Fox	0.016	0.017	0.013	-20.19	5,552
upLynk	0.014	0.013	0.016	20.99	7,977
DirecTV	0.013	0.012	0.023	97.85	1,332
Xbox	0.013	0.012	0.021	76.78	2,216
Dish Network	0.012	0.012	0.016	31.89	392
NBC	0.012	0.012	0.013	3.61	3,412
Microsoft	0.012	0.01	0.025	137.18	4,116

Notes: Unconditional average daily usage by application for all households, households that do not adopt Kodi, and households that adopt Kodi. Difference (%) is the percent difference between Kodi and non-Kodi households. Count is the number of households that ever engage with the application. Usage is measured in gigabytes.

Table 5 describes a breakdown of total TV viewership into categories, the largest of which are Network TV (ABC, CBS, FOX, NBC), News channels, Kids' channels, Daytime/Drama channels (Bravo, Hallmark, Lifetime, etc.), Movie channels, and Sports channels. The average household in the sample watches 4.33 hours of TV per day.

Table 5: TV Viewing by Category

	All HHs	Non-Kodi	Kodi	Difference (%)
Total	4.328	4.246	5.193	22.29
Network TV	1.315	1.306	1.413	8.24
News	0.436	0.443	0.363	-18.10
Kids	0.390	0.364	0.664	82.12
Daytime/Drama	0.311	0.306	0.362	18.44
Sports	0.264	0.257	0.331	28.80
Movie	0.259	0.254	0.318	25.33
Education/Science	0.234	0.230	0.286	24.53
Lifestyle	0.230	0.227	0.270	19.13
Music/Reality	0.162	0.151	0.284	87.91
General Entertainment	0.129	0.126	0.159	26.74
Premium	0.071	0.067	0.115	70.93
Outdoor	0.065	0.065	0.065	0.57
Spanish	0.002	0.002	0.002	11.63
Other	0.459	0.449	0.560	24.61

Notes: Average daily viewing of TV channel groups for all households, households that do not adopt Kodi, and households that adopt Kodi. Difference (%) is the percent difference between Kodi and non-Kodi households. Viewing is measured in hours.

2.4 Behavioral patterns among Kodi adopters

There is clear reason to believe household characteristics including content preferences, technological abilities, and demographic characteristics may drive selection into Kodi adoption. We describe behavioral differences between Kodi adopters and non-adopters and within-household changes that occur once a household adopts piracy technology.

Kodi users on average generate 70% more total internet traffic, 75% more RTE traffic, and 20% more TV traffic than other households (Table 2), suggesting more intense preferences for online and media content among households which engage with piracy. Additionally, fewer Kodi adopters (51%) than non-Kodi households (69%) are TV subscribers. While most large usage categories exhibit differences between Kodi adopters and non-adopters roughly proportional to the 70% total level difference, adopters engage substantially more with online gaming and bulk file transfers (Table 3).

Kodi users engage more heavily with Netflix (48% more), YouTube (76% more), Amazon Video (51% more) and Hulu (47% more) than non-users (Table 9). They engage substantially more with some applications, including Twitch (150% more), some online live TV providers (DirecTV Now, 159% more; PlayStation Vue 51% more), social media (Instagram, 341% more), and online sports programming (MLB, 100% more; ESPN, 51% more). Kodi users who have TV subscriptions also exhibit different TV preferences from other households, including at least 25% greater levels of engagement with the Premium, Kids, Music/Reality, Movie, and Sports genres (Table 5).

In the three months after a household uses Kodi for the first time, we observe a 14% increase in daily traffic relative to the preceding three months. During this period, RTE consumption increases by 14% while TV viewership declines by 8%. These within-household differences suggest persistent changes in media engagement following Kodi adoption. However, they are not interpretable as causal effects, as they do not account for a host of factors including aggregate usage growth, seasonality, and individual tastes that likely drive both Kodi adoption and media consumption decisions.

3 Empirical Analysis

In this section, we document the impact of piracy technology adoption on consumer behavior and firm revenues. The main empirical challenge in measuring these effects stems from the fact that although the arrival of Kodi technology is exogenous, the decision to adopt the technology is likely influenced by both household characteristics and seasonal factors. To account for this selection, we use a synthetic difference-in-differences approach, leveraging the long panel of pre-adoption observations to estimate household-specific counterfactual usage decisions. Throughout the section, we refer to those households that ever use the Kodi application as Kodi *adopters*. We use *adoption date* for the first date on which the application was used.

3.1 Subscription Choice and Expenditure

We first analyze the impact of Kodi adoption on service provider revenues. To the extent that Kodi technology is a substitute to the ISP's TV service, we may observe a reduction in TV expenditures due to TV subscription cancellations (cord-cutting) or downgrades to lower-revenue tiers of TV service with fewer channels. On the other hand, if internet download speed is a complement to Kodi usage (since faster speeds may be required to facilitate higher volumes of video streaming), internet expenditures may increase due to tier upgrades.

Table 6: The Effect of Kodi Adoption on ISP Expenditures

	TV		Internet		All Services	
	(1)	(2)	(3)	(4)	(5)	(6)
Kodi Adopter	-0.038***		0.041***		-0.010	
	(0.009)		(0.004)		(0.007)	
After Adoption	-0.101***	-0.032***	0.020***	0.009***	-0.059***	-0.010***
	(0.010)	(0.005)	(0.005)	(0.003)	(0.008)	(0.003)
Constant	4.426***	4.400***	3.849***	3.863***	4.846***	4.815***
	(0.006)	(0.002)	(0.003)	(0.001)	(0.005)	(0.001)
Household FE	No	Yes	No	Yes	No	Yes
Monthly Dummies	Yes	Yes	Yes	Yes	Yes	Yes
Observations	106,907	106,907	148,923	148,923	148,923	148,923

Notes: Results of OLS and household fixed-effect regressions of log monthly expenditures on ISP subscriptions by category (TV service, internet service, all expenditures) on a Kodi adoption indicator, household-level adoption indicator and monthly dummies.

To separate these two effect channels, we first regress log monthly expenditures on a Kodi adoption indicator and monthly dummies. We estimate separate specifications for TV and internet expenditures, in addition to the combination of expenditures on all ISP services. Table 6 reports coefficient estimates. On average, prior to the adoption date, Kodi adopters with TV subscriptions spend 3.7% less on TV than non-Kodi adopters with TV subscriptions. Also, Kodi adopters spend 4.2% more on internet service than non-adopters. Incorporating household fixed effects, we estimate a further 3.1% reduction in monthly TV payments among TV subscribers and a 0.9% increase in monthly internet payments among Kodi adopters after the adoption date. Pooling together expenditures, the average monthly bill paid by Kodi adopters decreases by 1% after the adoption date. We note that although the net revenue change is negative, the two service types have different profit margins, so the net effect on profit may not be negative (i.e., if the change in profit from the 3.2% revenue reduction among the 67% of households with TV does not exceed the profit increase associated with the 0.9% increase in revenue from internet households).

Table 7: The Effect of Kodi Adoption on ISP Subscriptions

	Add TV		Drop TV		Upgrade Internet	
	(1)	(2)	(3)	(4)	(5)	(6)
Kodi Adopter	0.037**	0.034*	0.026**	0.024**	0.053***	0.051***
	(0.019)	(0.018)	(0.013)	(0.012)	(0.015)	(0.014)
Constant	0.122***		0.096***		0.228***	
	(0.006)		(0.004)		(0.004)	
Observations	3,415	3,415	6,922	6,922	9,739	9,739

Notes: Results of household-level regressions describing changes in ISP subscriptions between the beginning and end of the sample period. Dependent variables indicate whether a given household took each action (new TV subscription, cancelled TV subscription, upgraded internet tier). Odd-numbered columns contain OLS coefficients; even-numbered columns contain Probit regression marginal effects. Specifications 1 and 2 contain households that start the sample with no TV subscription. Columns 3 and 4 contain households that start the sample with a TV subscription. Columns 5 and 6 contain all households except those that start the sample on the highest internet service tier.

We also document the impact of Kodi adoption on consumer subscription decisions. We regress household-level indicators of each type of subscription change (add TV, drop TV, upgrade internet tier) on the Kodi adoption indicator. Table 7 reports these results. We find that Kodi adopters add and cancel TV subscriptions, and that the number of cord-cuts exceeds the number of new TV subscriptions.[14]. We also find that the previously documented increase in internet expenditures is driven by an approximately 5% internet tier upgrade rate among Kodi adopters.

3.2 Media Engagement

3.2.1 Estimation Strategy

Our next goal is to understand whether observed changes in consumer behavior can be attributed to Kodi adoption. The main empirical challenge is that while the arrival of streaming devices outfitted with Kodi software is an exogenous introduction of new technology, the choice to adopt the technology and the timing of the adoption choice are clearly endogenous. To correct for household-level selection into the adopter group and any seasonal factors that contribute to adoption timing, we use a generalization of

[14] Although the rate of new TV subscriptions among internet-only households is larger than the cord-cutting rate among households with TV subscriptions, the number of households with TV subscriptions is more than twice the number who do not.

the synthetic control method, the synthetic difference in differences (SDID) approach of Arkhangelsky et al. (2021). The SDID method constructs a counterfactual estimate of the behaviors that would have been realized in the absence of adoption. These counterfactual estimates can then be used to estimate adoption treatment effects.

If we apply the traditional linear panel method, difference in differences, non-adopters cannot reproduce the "correct" counterfactual outcome that adopters would have exhibited in the absence of the event due to selection on adopter characteristics. To control for this selection, a synthetic control group must be constructed from a weighted average of non-adopters that exhibit the same pre-adoption behaviors as the adopters. The synthetic control group method developed by Abadie et al. (2010) is to calculate optimal weights that minimize the pre-adoption distance—the residual from using non-adopter observables to approximate adopter observables—and then to apply those weights to the outcomes ex-post. The original synthetic control method is best suited to the case of one treated unit, to which treatment is introduced at a fixed time. As we have multiple "treated" units, each of which is exposed to the "treatment" at a different time, we follow the more robust SDID method, a doubly-weighted synthetic control estimator with both household and time period weights. This combination allows us to approximate the behaviors of Kodi adopters using non-adopter behaviors during the pre-adoption period and weight time periods that most closely resemble the post-adoption periods for which we impute the counterfactuals.

The SDID estimator $\hat{\tau}^{sdid}$ can be seen as a weighted least squares regression estimator with household-specific and time-specific weights, where the regression model includes time and household fixed effects. With N total households, split between N_1 Kodi adopters and N_0 non-adopters, and T time periods, split between T_1 post-adoption time periods, and T_0 pre-adoption time periods, the model is formally defined as

$$(\hat{\mu}, \hat{\alpha}, \hat{\beta}, \hat{\tau}^{sdid}) = \arg\ \min_{\mu,\alpha,\beta,\tau} \sum_{i=1}^{N} \sum_{t=1}^{T} (Y_{it} - \mu - \alpha_i - \beta_t - W_{it}\tau)^2 \hat{\omega}_i \hat{\lambda}_t$$

Here Y_{it} is the outcome variable, total or categorical usage. W_{it} is a $N \times T$ treated block of 0 or 1, with each W_{it} indicating whether household i has adopted Kodi at time t. The ω_i and λ_t parameters are unit and time weights. The ω_i weights are chosen to make the weighted average of the controls in the pre-treatment period approximate the corresponding value for the treated household, i.e., $\sum_i \hat{\omega}_i Y_{it} \approx Y_{nt}$ for all $t \in \{1, ..., T_0\}$ and $n \in \{N_0 + 1, ..., N\}$. The λ_t weights are chosen such that within a household, the weighted average outcomes across time periods approximate the target, i.e., $\sum_t \hat{\lambda}_t Y_{it} \approx Y_{is}$ for all $i \in \{1, ..., N_0$ and $s \in \{T_0 + 1, ..., T\}$. The terms inside the parentheses form a two-way fixed effect model, incorporating both the unit and time weights of standard DID models and the unit fixed effects and time weights of synthetic control models.

The main difference between our approach and the SDID estimator outlined in Arkhangelsky et al. (2021) is our use of a household-specific (rather than common across all households) assignment matrix. This deviation is motivated by the fact that households adopt Kodi at different times throughout the sample period. The estimator we use to accommodate this staggered adoption is effectively a weighted average of household-specific SDID estimators.

3.2.2 Results

We estimate the average effect of Kodi adoption on internet and TV usage using 90-day pre- and post-adoption windows for each household. Our use of a long window to measure behavioral changes is motivated by previous work, which establishes that changes in internet media usage can occur well before (or after) new services are adopted, and enabled by our long panel (Malone et al., Forthcoming). Also, a longer observation period allows us to smooth over substantial inter-day variance in behaviors.

We report estimates using three approaches: standard difference-in-differences, synthetic controls, and SDID. We find no clear time trend in the Kodi adoption month, and report regression results without a treatment period indicator.

Table 8 reports the average effect of Kodi adoption on internet usage by traffic category and overall. In each regression, the number of treated households is 328, and the treatment effect is the difference between average usage in the 90 days preceding and

Table 8: The Effect of Kodi Adoption on Internet Usage

	SDID	SC	DID	Count
Total	2.88 (0.513)	2.88 (0.657)	3.02 (0.523)	328
Bulk Transfer	0.616 (0.159)	0.611 (0.16)	0.42 (0.133)	328
Email	0.007 (0.002)	0.007 (0.003)	0.008 (0.002)	328
Gaming	0.06 (0.053)	0.036 (0.065)	-0.035 (0.049)	328
Miscellaneous	0.069 (0.039)	0.056 (0.036)	0.053 (0.039)	328
Cloud	0.065 (0.039)	0.04 (0.039)	0.03 (0.036)	328
Peer-to-peer	-0.02 (0.02)	-0.031 (0.011)	-0.018 (0.015)	328
RTC	0.079 (0.026)	0.072 (0.045)	0.075 (0.022)	328
RTE	1.724 (0.346)	1.725 (0.484)	1.95 (0.361)	328
Social Media	0.044 (0.01)	0.037 (0.017)	0.035 (0.009)	328
Tunnel	0.026 (0.034)	0.009 (0.063)	0.037 (0.035)	328
Web Browsing	0.477 (0.13)	0.461 (0.151)	0.464 (0.12)	328

Notes: Estimates of the average effect of Kodi adoption on daily internet usage (measured in gigabytes) by category using SDID, SC, and DID methods. Standard errors computed using the jackknife estimator in parentheses. We use a 90-day pre- and post-adoption period. Count is the number of Kodi adopters used in each regression.

the 90 days following Kodi adoption.[15] Total usage increases by 2.88 gigabytes per day (25% of the average Kodi adopter's baseline) after a household adopts Kodi technology, and usage increases in nearly all individual traffic categories. The bulk of the increase comes from the RTE category, which sees a 1.72 gigabyte per day increase, followed by the Bulk Transfer category (0.62 gigabytes per day increase) and Web Browsing category (0.48 gigabytes per day increase). The large increase in RTE traffic (23% of the baseline Kodi adopter usage level) is not surprising given that the category makes up the majority of total usage for the average household, and an even higher proportion for Kodi users. Also, if households are adopting pirated video content to replace content they were already consuming on TV, the increase in streaming video intensity may be a natural result of substituting pre-existing consumption to the Kodi platform. The Bulk Transfer and Web browsing treatment effects are 46% and 38% increases over the adopter baseline, respectively. It is likely that some pirated media content accessed via Kodi is classified by the data processor as Bulk Transfer traffic. Other categories with positive and statistically significant, yet smaller-magnitude, treatment effects include Email, Real-time Communication, and Social Media.

We next look within the RTE traffic category and decompose video streaming traffic into individual applications and sub-categories. In creating the decomposition, we attempt to balance granularity with sample size, as most individual applications have relatively few subscribers. We estimate Kodi treatment effects for subscription video on demand (SVOD) services (Netflix, Amazon Video, Hulu, etc.), live channels (streaming websites associated with individual television networks, e.g., nbc.com, and bundles of live channels delivered via streaming, e.g., Sling TV, DirecTV Now, etc.), YouTube, movie applications, gaming (primarily Twitch.tv), and social media streaming.

The streaming application treatment effect estimates are presented in Table 9. We see a large and significant increase in SVOD traffic, an increase of 0.52 gigabytes per day which is driven primarily by Netflix consumption. We do not observe a significant increase in the consumption of other major SVOD applications including Amazon Video

[15] The treatment effect estimates are robust to period length. The appendix contains additional regression tables for alternative durations.

Table 9: The Effect of Kodi Adoption on Digital Media Engagement

	SDID	SC	DID	Count
SVOD	0.523	0.523	0.554	308
	(0.209)	(0.256)	(0.201)	
Netflix	0.571	0.57	0.557	277
	(0.187)	(0.236)	(0.179)	
Amazon Video	0.097	0.07	0.061	192
	(0.132)	(0.124)	(0.138)	
Hulu	-0.008	-0.021	-0.034	72
	(0.213)	(0.176)	(0.208)	
Live Channels	0.247	0.238	0.154	266
	(0.102)	(0.13)	(0.096)	
Youtube	0.569	0.566	0.912	328
	(0.163)	(0.291)	(0.153)	
Subscription/Free Movies	0.032	0.002	0.036	120
	(0.022)	(0.043)	(0.022)	
	0.149	0.14	0.337	

Notes: Estimates of the average effect of Kodi adoption on daily engagement with media content providers (measured in gigabytes) using SDID, SC, and DID methods. Standard errors computed using the jackknife estimator in parentheses. We use a 90-day pre- and post-adoption period. Count is the number of Kodi adopters used in each regression. Households must record at least 5 days of positive usage of the content source to be included. SVOD includes Netflix, Amazon Video, and Hulu. Live channels includes all TV network affiliate websites (e.g., HBO, ESPN, etc.) and streaming TV bundles (e.g., Sling TV, DirecTV Now, etc.). Subscription/Free Movies includes on-demand movie streaming websites (e.g., Fandango, Vudu, etc.).

and Hulu. YouTube traffic also increases substantially, with similar magnitude to the overall SVOD increase (0.57 gigabytes per day). We observe a significant increase in usage of network channel streaming content, suggesting that households may substitute viewership that would have otherwise happened on traditional TV to streaming.

We next look at behavioral changes in TV viewership. Total TV consumption actually increases on average in the 90 days surrounding Kodi adoption, though the effect is not significant. We group individual channels by theme, with the categories explained in the appendix and results reported in Table 10. Relatively few Kodi adopters subscribed to the MSO's TV service even before adopting Kodi software, so sample sizes for these regressions are relatively small. We see few significant effects in the individual categories, suggesting there is not a clear effect of Kodi adoption on TV consumption.

3.2.3 Placebo Evaluation

Our empirical environment differs from those studied in Arkhangelsky et al. (2021) along several dimensions, most notably because household adoption of Kodi technology is staggered rather than in a single time period. As such, each "treated" household has a variable adoption date and a variable treatment period length. Our main empirical specifications use a 90-day usage panel both before and after the adoption date. This relatively long pre- and post-adoption panel leads to better usage estimates for each household, but a shorter panel duration would allow us to use more households, since some adoption occurs either at the beginning or the end of our sample period. Since we observe a limited number of Kodi adopters, and the sample size used in each model is directly determined by these duration parameters, we evaluate the implications of these choices for our results in a placebo study and robustness checks.

To check the robustness of our estimation procedure to sample size, treatment length, and adoption date, we first compare the performance of the SDID, SC, and DID estimators under a variety of sampling parameters. Specifically, for combinations of N_1 (number of treated households) and $T = T_0 = T_1$ (pre- and post-treatment duration), we randomly sample the full set of non-Kodi adopters, randomly assign each of the N_1 placebo treated

Table 10: The Effect of Kodi Adoption on TV Viewership

	SDID	SC	DID	Count
Total	0.156 (0.259)	0.171 (0.375)	-0.189 (0.22)	125
Premium	0.015 (0.248)	-0.019 (0.156)	0.129 (0.221)	22
Movie	-0.014 (0.118)	-0.013 (0.137)	-0.045 (0.119)	92
News	-0.215 (0.205)	-0.242 (0.206)	-0.337 (0.233)	76
Sports	-0.037 (0.123)	-0.029 (0.149)	-0.063 (0.157)	79
Kids	0.214 (0.2)	0.241 (0.388)	-0.003 (0.205)	58
Music/Reality	0.281 (0.142)	0.249 (0.175)	0.36 (0.175)	77
Lifestyle	0.359 (0.252)	0.378 (0.328)	0.465 (0.253)	65
Network TV	-0.117 (0.118)	-0.127 (0.131)	-0.226 (0.133)	118
Education/Science	-0.231 (0.13)	-0.271 (0.165)	-0.194 (0.145)	70
Daytime/Drama	0.197 (0.24)	0.193 (0.261)	0.07 (0.228)	81
General Entertainment	0.157 (0.199)	0.142 (0.248)	0.105 (0.187)	64

Notes: Estimates of the average effect of Kodi adoption on daily TV viewership (measured in hours) using SDID, SC, and DID methods. Standard errors computed using the jackknife estimator in parentheses. We use a 90-day pre- and post-adoption period. Count is the number of Kodi adopters used in each regression. Households must record at least 5 days of engagement with the TV network category to be included.

households a treatment adoption date, and attempt to estimate “counterfactual” total internet usage for each treated household. We compare our model’s predictions to the true empirical outcomes and summarize the performance of the estimators in terms of RMSE and bias in Table 11.

Table 11: Placebo Studies

			SDID		SC		DID	
N_0	N_1	T	RMSE	Bias	RMSE	Bias	RMSE	Bias
3000	50	60	1.031	-0.004	1.030	-0.010	1.116	-0.002
3000	100	60	0.765	-0.003	0.766	-0.009	0.825	0.000
3000	250	60	0.496	-0.010	0.496	-0.004	0.535	0.003
3000	500	60	0.367	-0.008	0.366	-0.002	0.393	0.002
3000	50	90	1.099	-0.009	1.094	-0.013	1.154	0.004
3000	100	90	0.794	-0.000	0.793	-0.007	0.838	0.001
3000	250	90	0.515	-0.003	0.515	-0.002	0.543	0.003
3000	500	90	0.378	-0.005	0.378	-0.004	0.399	0.001

Notes: Results of placebo simulations to predict total internet usage of Kodi non-adopters. The number of “control” households (N_0) is fixed at 3,000, while the number of “treated” households (N_1) and the duration of the prediction window (T) vary. Each treated household is randomly assigned a treatment start date during the sample period. All RMSE and Bias results are based on 500 simulation replications.

Broadly speaking, we find that all three estimators have strong performance under the sampling parameters used for our main results, both in terms of bias and RMSE. Decreasing T from 90 to 60 does not negatively impact these measures of fit, though decreasing the number of treated households does raise RMSE. Comparing the three estimators, it appears that SDID and SC perform slightly better than DID, but the difference between the SDID and SC results appears negligible.

3.3 Discussion

The lawsuits brought by content providers and MSOs suggest that Kodi-ready streaming boxes facilitated piracy and meaningfully impacted the profitability of content production and distribution. Yet, as has been the case with many past claims of damages due to piracy, there was no direct empirical evidence to demonstrate economic harm. Our results provide insight into the trade-offs that Kodi introduced, and whether the lawsuits were in the best interests of the filing parties.

For content producers, the incentive to sue depends on whether Kodi was primarily a facilitator of piracy, or a platform to more conveniently and legally access and engage digital content. Our findings are mixed, and suggest that adoption of Kodi devices led to both an increase in legal engagement with content and an increase in traffic typically associated with piracy (i.e., the Bulk Transfer traffic category). Specifically, we find a large increase in RTE traffic following adoption, much of which is driven by prominent SVOD services like Netflix. The only category of traffic with a negative point estimate was live TV streaming services like Hulu, but the effect was small and statistically insignificant. Overall, this suggests that legal consumption of digital content over the internet actually increased, even if it was accompanied by an increase in piracy. However, we also find that consumption of digital content through TV services offered by MSOs is impacted on the extensive margin, with Kodi adopters more likely to cut the cord. This disproportionately impacts content producers that distribute mainly through MSO TV services via a reduction in advertising and licensing revenues.

The impact on content producers is less clear in the longer term. While RTE traffic increased, the statistically significant increase in bulk transfer traffic is likely due in part to engagement with illegally acquired content. If this increase represents an exploration of piracy as a substitute for legal access, it could diminish engagement in the future. The duration of our panel data limits our ability to explore this completely, but we find no evidence of such an effect in the 90-day window following adoption. Given the limits now placed on the distribution of pre-loaded Kodi boxes, it may be difficult to ever observe whether the role of the technology shifted for households over time. If the trend of cord-cutting after adoption were to continue, it would further the disproportionate impact on content distributed through MSO's TV service. This is likely to impact small content producers with fewer resources that rely on the MSO as a platform for distribution. If variety is highly valued by consumers, this could have negative consequences in the longer term.

The trade-off for MSOs is complex but directly observed in our data. Although Kodi boxes require internet access, and see improved performance with faster connection speeds, they also serve as a low-cost alternative to the MSO's TV service (i.e., either by facilitating piracy or legal OTT video access). Thus, whether the technology is used for piracy, it increases demand for internet services and decreases demand for TV service. We estimate both effects of Kodi adoption: changes in the probability of internet tier upgrades and TV service cancellations. Whether the MSO is made better or worse off depends on the relative margins of the two services. Internet service is largely a fixed-cost service, and as such, upgrades to higher service tiers come with little to zero change in cost given that a household is already connected. In contrast, TV service has substantial marginal costs due to licensing fees paid to content producers for each subscribing customer.

This makes it possible to calculate a threshold margin on TV services that would make Kodi adoption harmful for MSOs. Specifically, we find that Kodi adopters spend \$1.84 less on TV per month and \$0.57 more on internet per month. If we assume that \$0.57 revenue change is fully realized as profit, i.e., tier upgrades have zero marginal cost, then the MSO is better off if the margin on TV is less than $\frac{\$0.57}{\$1.84}$, or 31%. For many smaller MSOs, 31% margins for TV service are unlikely because of the relative negotiating power of large content producers (e.g., Disney). For MSOs with larger numbers of subscribers these margins are plausible, especially for vertically-integrated MSOs like Comcast and AT&T that receive a portion of their content at zero marginal cost. Therefore, we would expect the majority of any potential harm to be realized by larger vertically-integrated MSOs that also experience lost licensing revenue due to cord-cuts. Limitations on application-specific pricing to mitigate Kodi adoption or profit from it, due to concerns regarding net neutrality regulation and DMCA consequences, left litigation as the only practical strategy for MSOs to reduce these losses. The complementary actions taken by government and other private entities like Google to limit Kodi adoption while the lawsuits were decided were helpful in reducing harm that could impact investment in broadband networks.

4 Conclusion

Many industries rely on IP and copyright law to encourage innovation and investment. In the case of digital goods, for which replication is low-cost and unlicensed access is difficult to detect, these protections are challenging to enforce. Our unique panel data reveal the timing of adoption of Kodi-ready streaming boxes for a large set of households, and provide detailed records of media consumption before and after adoption. Our empirical findings identify multiple parties which gain from or are harmed by media piracy.

In the short run, consumers who adopted Kodi obviously benefited from low-cost access to content. Also, many large SVOD services including Netflix appear to have benefited from Kodi adoption in spite of their support of lawsuits alleging damages. MSOs with low TV margins relative to internet margins benefitted from increased demand for internet services, while larger MSOs with higher TV margins, and content producers that rely on the MSO for distribution, were harmed by reduced demand for TV. In the long run, the directions and magnitudes of these effects are less clear because the market for Kodi-ready streaming boxes collapsed quickly after litigation and other efforts. The length of our panel provides some evidence that the short-run effects have at least some stability over time.

There remains considerable opportunity for complementary future research. As new technologies facilitating illegal access to digital goods emerge, similar difficulties will continue with regard to detection and quantification of damages. MSOs can play an important role in both aspects, and future research can help guide the evolution of policy while balancing consumer privacy concerns. As McManus et al. (2022) demonstrate for the case of OTT video, it is important to monitor MSO incentives regarding the neutrality of network content and how they evolve with emerging new technologies. Empirical studies documenting these incentives going forward will be important contributions to ongoing policy discussions.

References

Abadie, Alberto, Alexis Diamond and Jens Hainmueller (2010). "Synthetic Control Methods for Comparative Case Studies: Estimating the Effect of California's Tobacco Control Program." *Journal of the American Statistical Association*, 105(490): 493–505.

Arkhangelsky, Dmitry, Susan Athey, David A. Hirshberg, Guido W. Imbens and Stefan Wager (2021). "Synthetic Difference-in-Differences." *American Economic Review*, 111(12): 4088–4118.

Bakos, Yannis and Erik Brynjolfsson (2000). "Bundling and Competition on the Internet." *Marketing Science*, 19(1): 63–82.

Cunningham, Scott and Manisha Shah (2018). "Decriminalizing Indoor Prostitution: Implications for Sexual Violence and Public Health." *The Review of Economic Studies*, 85(3): 1683–1715.

Danaher, Brett and Joel Waldfogel (2012). "Reel Piracy: The Effect of Online Film Piracy on International Box Office Sales." *Available at SSRN 1986299.*

Dutz, Mark A, Jonathan M Orszag and Robert D Willig (2012). "The Liftoff of Consumer Benefits from the Broadband Revolution." *Review of Network Economics*, 11(4): 1–34.

Edell, Richard and Pravin Varaiya (1999). "Providing Internet Access: What We Learn from INDEX." *IEEE Network*, 13(5): 18–25.

Goetz, Daniel (2019). "Dynamic Bargaining and Size Effects in the Broadband Industry." *Available at SSRN 3332461.*

Goolsbee, Austan and Peter J Klenow (2006). "Valuing Products by the Time Spent Using Them: An Application to the Internet." *American Economic Review*, 96(2): 108–113.

Greenstein, Shane and Ryan C McDevitt (2011). "The Broadband Bonus: Estimating Broadband Internet's Economic Value." *Telecommunications Policy*, 35(7): 617–632.

Greenstein, Shane, Martin Peitz and Tommaso Valletti (2016). "Net Neutrality: A Fast Lane to Understanding the Trade-Offs." *Journal of Economic Perspectives*, 30(2): 127–50.

Hitt, Lorin and Prasanna Tambe (2007). "Broadband Adoption and Content Consumption." *Information Economics and Policy*, 74(6): 1637–1673.

Lee, Robin S and Tim Wu (2009). "Subsidizing Creativity through Network Design: Zero-Pricing and Net Neutrality." *Journal of Economics Perspectives*, 23(3): 61–76.

Leung, Tin Cheuk (2015). "Music Piracy: Bad for Record Sales but Good for the iPod?" *Information Economics and Policy*, 31: 1–12.

Malone, Jacob B., Aviv Nevo, Zachary Nolan and Jonathan W. Williams (Forthcoming). "Is OTT Video a Substitute for TV? Policy Insights from Cord-Cutting." *The Review of Economics and Statistics.*

Malone, Jacob B., Aviv Nevo and Jonathan W Williams (2021). "The Tragedy of the Last Mile: Economic Solutions to Congestion in Broadband Networks." *Working Paper.*

Malone, Jacob B., John L Turner and Jonathan W Williams (2014). "Do Three-Part Tariffs Improve Efficiency in Residential Broadband Networks?" *Telecommunications Policy*, 38(11): 1035–1045.

McManus, Brian, Aviv Nevo, Zachary Nolan and Jonathan W Williams (2022). "The Steering Incentives of Gatekeepers in the Telecommunications Industry." *Working Paper.*

Nevo, Aviv, John L Turner and Jonathan W Williams (2016). "Usage-Based Pricing and Demand for Residential Broadband." *Econometrica*, 84(2): 411–443.

Oberholzer-Gee, Felix and Koleman Strumpf (2007). "The Effect of File Sharing on Record Sales: An Empirical Analysis." *Journal of Political Economy*, 115(1): 1–42.

Oberholzer-Gee, Felix and Koleman Strumpf (2016). "The Effect of File Sharing on Record Sales, Revisited." *Information Economics and Policy*, 37(C): 61–66.

Peitz, Martin and Patrick Waelbroeck (2004). "The Effect of Internet Piracy on CD Sales: Cross-section Evidence." *Available at SSRN 511763*.

Prince, Jeffrey and Shane Greenstein (2017). "Measuring Consumer Preferences for Video Content Provision via Cord-Cutting Behavior." *Journal of Economics & Management Strategy*, 26(2): 293–317.

Rob, Rafael and Joel Waldfogel (2006). "Piracy on the High C's: Music Downloading, Sales Displacement, and Social Welfare in a Sample of College Students." *Journal of Law and Economics*, 49(1): 29–62.

Rob, Rafael and Joel Waldfogel (2007). "Piracy on the Silver Screen." *The Journal of Industrial Economics*, 55(3): 379–395.

Rosston, Gregory L, Scott J Savage and Bradley S Wimmer (2013). "Effect of Network Unbundling on Retail Price: Evidence from the Telecommunications Act of 1996." *Journal of Law and Economics*, 56(2): 487–519.

Sandvine (2017). "Global Internet Phenomena Spotlight: The "Fully-Loaded" Kodi Ecosystem." Technical report.

Shapiro, Carl, Hal R Varian, Shapiro Carl et al. (1998). *Information Rules: A Strategic Guide to The Network Economy*. Harvard Business Press.

Takeyama, Lisa N (1997). "The Intertemporal Consequences of Unauthorized Reproduction of Intellectual Property." *Journal of Law and Economics*, 40(2): 511–22.

Tudon, Jose (2021). "Prioritization vs. Congestion on Platforms: Evidence from Amazon's Twitch.tv." *Working Paper*.

Varian, Hal R (2000). "Buying, Sharing and Renting Information Goods." *The Journal of Industrial Economics*, 48(4): 473–488.

Varian, Hal R (2002). *The Demand for Bandwidth: Evidence from the INDEX Experiment*, volume Broadband: Should We Regulate High-Speed Internet Access? Brookings Institution.

Waldfogel, Joel (2012). “Copyright Protection, Technological Change, and the Quality of New Products: Evidence from Recorded Music since Napster.” *Journal of Law and Economics*, 55(4): 715–740.

Zentner, Alejandro (2006). “Measuring the Effect of File Sharing on Music Purchases.” *Journal of Economics Perspectives*, 49(1): 63–90.

A Robustness Checks

We replicate our three main results tables using a shorter usage panel of 60 days before and after adoption rather than the 90-day panel used in the main text. This change results in no meaningful differences in estimated coefficients or standard errors. The results tables are included below.

Table 12: Bucket DID Estimates, 60 Days Before and After, No Time Control

	SDID	SC	DID
Total	2.732	2.732	2.58
	(0.506)	(0.649)	(0.507)
Bulk Transfer	0.537	0.527	0.361
	(0.151)	(0.18)	(0.143)
Email	0.006	0.006	0.007
	(0.002)	(0.003)	(0.002)
Gaming	0.064	0.037	-0.051
	(0.058)	(0.067)	(0.058)
Miscellaneous	0.056	0.041	0.021
	(0.033)	(0.027)	(0.036)
Cloud	0.04	0.012	0.002
	(0.031)	(0.032)	(0.025)
Peer-to-peer	-0.021	-0.037	-0.019
	(0.031)	(0.013)	(0.015)
RTC	0.074	0.065	0.063
	(0.024)	(0.044)	(0.021)
RTE	1.711	1.71	1.743
	(0.343)	(0.473)	(0.35)
Social Media	0.032	0.026	0.025
	(0.009)	(0.018)	(0.009)
Tunnel	0.061	0.054	0.053
	(0.043)	(0.063)	(0.041)
Web Browsing	0.39	0.367	0.374
	(0.119)	(0.153)	(0.102)

Notes: This table shows 60-day synthetic diff-in-diff, synthetic control and diff-in-diff results for bucket data. A jackknife estimate of standard errors is in the parenthesis. Number of Kodi units: 328 Threshold: $>$ 30days.

Table 13: RTE DID Estimates, 60 Days Before and After, No Time Control

	SDID	SC	DID
SVOD	0.444	0.444	0.355
	(0.214)	(0.256)	(0.2)
Netflix	0.52	0.52	0.337
	(0.194)	(0.237)	(0.181)
Amazon Video	0.134	0.112	0.105
	(0.151)	(0.142)	(0.161)
Hulu	-0.216	-0.222	-0.005
	(0.25)	(0.209)	(0.237)
Live Channels	0.338	0.328	0.321
	(0.141)	(0.188)	(0.126)
Youtube	0.67	0.651	0.838
	(0.168)	(0.295)	(0.158)
Subscription/Free Movies	0.065	0.038	0.064
	(0.044)	(0.074)	(0.043)
	0.119	0.118	0.368

Notes: This table shows 60-day synthetic diff-in-diff, synthetic control and diff-in-diff results for rte data. A jackknife estimate of standard errors is in the parenthesis. Threshold: > 5days.

Table 14: TV Network Treatment Effects

	SDID	SC	DID
Total	0.209	0.21	-0.11
	(0.265)	(0.411)	(0.23)
Premium	-0.04	-0.053	0.127
	(0.253)	(0.161)	(0.2)
Movie	-0.011	-0.013	-0.049
	(0.126)	(0.11)	(0.123)
News	-0.168	-0.204	-0.224
	(0.169)	(0.2)	(0.208)
Sports	0.014	0.018	-0.027
	(0.154)	(0.166)	(0.17)
Kids	0.153	0.148	-0.038
	(0.222)	(0.399)	(0.207)
MusicReality	0.427	0.413	0.567
	(0.155)	(0.219)	(0.174)
Lifestyle	0.33	0.307	0.393
	(0.257)	(0.345)	(0.261)
NetworkTV	-0.088	-0.089	-0.183
	(0.132)	(0.145)	(0.142)
EducationScience	-0.244	-0.278	-0.225
	(0.153)	(0.194)	(0.184)
DaytimeDrama	0.15	0.162	0.038
	(0.262)	(0.261)	(0.25)
GeneralEntertainment	0.07	0.081	0.004
	(0.183)	(0.251)	(0.133)

Notes: This table shows 60-day synthetic diff-in-diff, synthetic control and diff-in-diff results for TV viewing data. A jackknife estimate of standard errors is in the parenthesis. Threshold: $>$ 30days.