Department of Economics- FEA/USP

Is video streaming hurting box office revenues at U.S. theaters?

Gabriela Duarte de Souza
Marislei Nishijima
Mauro Rodrigues

Working Paper Series Nº 2024-20

DEPARTMENT OF ECONOMICS, FEA-USP
WORKING PAPER Nº 2024-20

Is video streaming hurting box office revenues at U.S. theaters?

Gabriela Duarte de Souza (gabriela-duarte@usp.br)

Marislei Nishijima (marislei@usp.br)

Mauro Rodrigues (mrodrigues@usp.br)

Abstract:

Given the scarcity of data on video streaming consumption, few studies have attempted to measure its effects on other traditional film media. To overcome this literature gap, we evaluate the impact of streaming indirectly by exploring the early introduction of Netflix streaming services in the U.S. as an intervention. We use the Australian market as a comparison group, given that Netflix was not available in that country until 2015. Using a sample of films released in the U.S. and Australia between 2004 and 2014, we document that the launch of Netflix streaming services in 2007 is associated with a reduction of 14 to 17% in box office revenues.

Keywords: Streaming video, Netflix, cinema, films, technology, movie theaters

JEL Codes: L8, L82, L86, O33.

Is video streaming hurting box office revenues at U.S. theaters?

Corresponding author: Gabriela Duarte de Souza
School of Arts, Sciences and Humanities - University of Sao Paulo
gabriela-duarte@usp.br, ORCID: 0000-0003-0495-1324

Marislei Nishijima
Institute of International Relations - University of Sao Paulo
marislei@usp.br, ORCID: 0000-0003-1162-7987

Mauro Rodrigues
Department of Economics - University of Sao Paulo
mrodrigues@usp.br, ORCID: 0000-0003-3745-3989

Abstract: Given the scarcity of data on video streaming consumption, few studies have attempted to measure its effects on other traditional film media. To overcome this literature gap, we evaluate the impact of streaming indirectly by exploring the early introduction of Netflix streaming services in the U.S. as an intervention. We use the Australian market as a comparison group, given that Netflix was not available in that country until 2015. Using a sample of films released in the U.S. and Australia between 2004 and 2014, we document that the launch of Netflix streaming services in 2007 is associated with a reduction of 14 to 17% in box office revenues.

Keywords: Streaming video, Netflix, cinema, films, technology, movie theaters

JEL Classification L8; L82; L86; O33

The datasets generated and/or analyzed during the current study are available from the corresponding author upon reasonable request. We thank two anonymous referees for helpful comments and suggestions.

1. Introduction

Streaming video has become a pervasive technology, offering instantaneous video transmission over networks. This innovative service enables consumers to enjoy movies more swiftly than traditional internet access methods that involve content downloads. Undoubtedly, this marks a revolutionary shift in the way we consume video content, making it possible to watch a movie on different gadgets (such as mobiles or tablets), at any time and place (Waldfogel 2017a, 2017b).

Nonetheless, our understanding of various aspects, such as content specifics, subscriber counts, preferences, viewing habits, and the consequent effects on established media channels, remains somewhat limited. This arises primarily because streaming giants like Netflix, Prime Video, Disney+, among others, choose not to divulge comprehensive information about their consumption patterns. As a result, comprehending the full extent of their impact on the media industry proves to be a challenge.

The present paper investigates the effect of streaming video on U.S. movie theater consumption, employing publicly available data between 2004 to 2014. Specifically, we use the year that Netflix launched its video streaming services (2007) in the U.S. as an intervention. The U.S. film industry provides an important case study. Not only is it the birthplace of pioneering video streaming companies, but it also remains the dominant player in the global film industry, generating the highest revenues worldwide.[1]

Netflix pioneered offering video streaming services to a significant portion of the U.S. population, making it the market leader in the streaming industry (McKenzie et al. 2023).[2] Between

[1] https://www.statista.com/statistics/243180/leading-box-office-markets-workdwide-by-revenue/

[2] Although Hulu was also launched in the U.S. in 2007, we chose to focus on Netflix due to its dominance in the market.

2007 and 2019, the number of Netflix subscriptions increased eightfold, reaching 61 million in 2019 (see Figure 1). If we assume 2.6 persons per household (data from the U.S. Census) and that everyone in a household has access to the service, that would amount to nearly 50% of the U.S. population being exposed to Netflix. These figures are even more striking considering that nowadays consumers have many more streaming platforms to choose from.

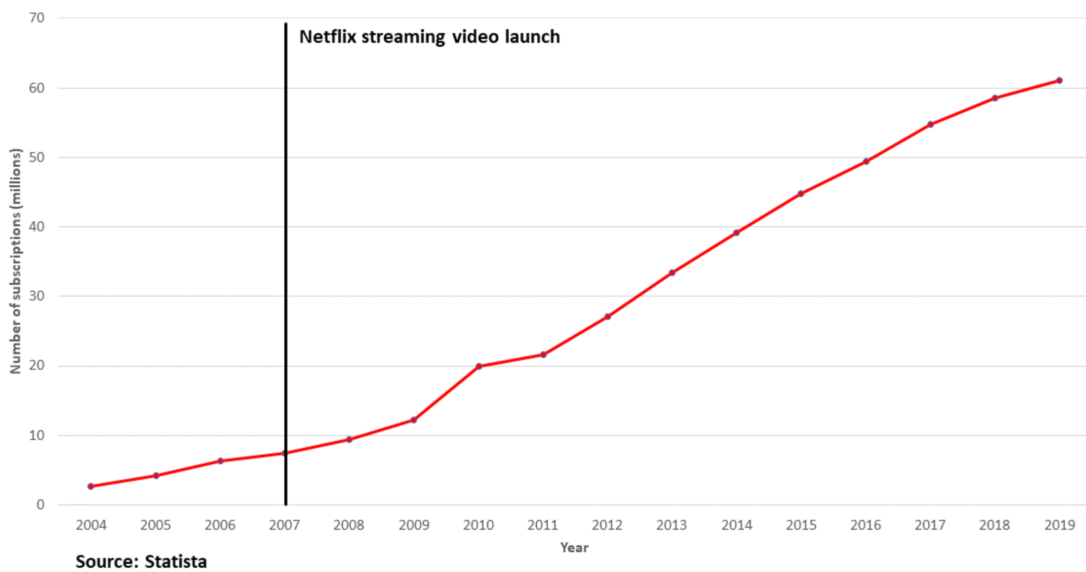


Figure 1 – Number of Netflix subscribers (millions)

Our empirical strategy employs the Australian market as a comparative baseline, capitalizing on its significant commonalities with the U.S. These similarities include shared language, colonial roots, cultural traditions, religious landscapes, and high living standards. These parallels make Australia a suitable reference point for a nuanced comparative analysis, facilitating a deeper understanding of the market dynamics within similar socio-economic contexts (Holloway 2014; Disdier et al. 2009). However, a crucial difference from the U.S. in our case is that Netflix was introduced in Australia only in 2015. Thus, our strategy assumes that, prior to 2007, films were not exposed to Netflix either in the U.S. or in Australia; from 2007, only movies shown in U.S. theaters were potentially affected by the intervention.

We use box office data from movies released in the U.S. and Australia between 2004 and 2014. We focus on widely released films, that is, those exhibited in more than 600 theaters throughout the U.S. during opening weekend, because we have more information about them. Our results indicate that streaming is a substitute for the consumption of films at theaters. The introduction of Netflix streaming services in 2007 is associated with a reduction of 14 to 17% in domestic box office revenues.

The proposed investigation presents several challenges, but we have taken steps to address them. An important challenge is the lack of data on country-specific film consumption at theaters in the U.S. Thus, we utilized the available data to conduct our analysis, relying on joint film consumption data for the U.S. and Canada (as reported by the boxofficemojo.com) to study the U.S. market. However, we argue that our approach is still valid and likely underestimates the impact of streaming.

To lend credence to our empirical strategy, we conduct a series of estimation exercises. Specifically, we (i) check for parallel trend issues; (ii) conduct permutation tests; (iii) evaluate whether our results are robust to the inclusion of movie fixed effects to the regressions; (iv) examine two competing explanations – the 2008 global financial crisis (GFC) and the first introduction of Netflix's original production to the platform in 2011.

Streaming provides a cheap and easy way to watch movies. For instance, a monthly Netflix subscription costs from USD 7 to USD 20 in the U.S. and gives access to a whole array of movies, series and documentaries that can be watched multiple times. Compare this with a cinema ticket, whose average price sits at around USD 10, but allows a person to watch only one movie once, at a specific venue and time.[3] Arguably, however, consuming a film at a theater is a very distinct experience from consuming it at home at any time (Kim and Kim 2017). In other words, it is a priori unclear to what extent streaming and cinema are substitutes. Our results suggest that this substitution exists and is quantitatively meaningful.

2. Related Literature

Recent technological advances – exemplified by the advent of Big Data, Artificial Intelligence, the Internet of Things, 5G, and Industry 4.0 – have facilitated the emergence of numerous new products and businesses involving information goods (Waldfogel, 2017a; Waldfogel, 2017b; Hadida et al., 2020). Waldfogel (2017a, 2017b) posits that the disruptive evolution in digitizing information goods – such as films, music, and books[4] – has ushered in a new era of success for these goods while also fostering the creation of new alternative or substitute goods.[5]

Digitalization lowers substantially the costs of reproducing and distributing content. In principle, the effect on traditional media is ambiguous. On the one hand, digital goods provide a cheaper alternative, leading consumers to substitute away from other forms of delivering content. On the other hand, digitalization propels information externalities: as more people get to know a

[3] For Netflix subscription prices, see https://help.netflix.com/en/node/24926/us. The average movie ticket price is from boxofficemojo.com. Appendix Figure A.1 brings more information on the price difference between a movie ticket and a Netflix subscription (per person), supposing that the subscription provides access to streaming for all members of a household.
[4] According to Varian (2005), films, music, books are information goods, since they can be digitized, transferred, and stored in bites.
[5] Our review focuses on music and especially video, but there are relevant contributions for other media. See, for instance, Gentzkow (2007) and Deleersnyder et al. (2002) for newspapers, and Chen et al. (2019) for books.

movie or song, they can increase its overall consumption through word of mouth – which potentially benefits traditional media.

In the early years of the Internet, the focus was on the effects of illegal file sharing on the music industry. Most papers in the literature suggest a dominant substitution effect, which is in line with the heavy revenue losses suffered by the music industry in the late 1990s and early 2000s. See, for instance, Rob and Waldfogel (2006), Zentner (2006), Waldfogel (2010), Liebowitz (2016).[6]

The movie industry, at first, remained somewhat insulated, given the large files associated with illegally downloading a movie (Waldfogel 2017b; McKenzie 2023). This scenario changed in the mid-2000s, with the increase in internet speeds and the development of P2P protocols such as BitTorrent, which allow pieces of a single large file to be downloaded from multiple users (Danaher and Waldfogel 2012). Based on survey data from university students, Rob and Waldfogel (2007) identify that piracy displaces movie consumption from legal sources.

Other papers find similar results relying on box office data. Using data on the number of pirate copies available online, De Vany and Walls (2007) find that piracy harms box office performance in the U.S. Danaher and Waldfogel (2012) take an indirect approach by exploring differences in release dates across countries, as pirated copies are made available earlier in countries with later release dates. They find that these delays are associated with lower box office revenues and, more importantly, that this effect became stronger after 2003 (when BitTorrent was introduced). Ma et al. (2014) reach similar conclusions using data on U.S. box office and piracy activity before the movie's release (for instance, from official copies that are leaked to pirate websites). Yue (2020) reports a negative correlation between piracy intensity and box office

[6] Oberholzer-Gee and Strumpf (2007) is an exception.

revenues in China, and that anti-piracy measures from the Chinese government are associated with stronger box office performance.

Ma et al. (2016) suggest that these strong substitution effects come basically from commercial releases. The effect of piracy on revenues is insignificant for niche movies (limited releases), which tend to rely more heavily on word of mouth. This indicates that the information externality channel is relevant, although outweighed by the substitution effect. Similarly, Peukert et al. (2017) explore the shutdown of a popular file-sharing platform (Megaupload) in 2012 to empirically evaluate the impact of piracy. They report evidence that this event increased revenues for wide releases (in line with the substitution effect) but reduced them for niche movies (in line with the information externality effect).

The rise in internet speeds also paved the way for streaming services, such as Spotify and Deezer for music, and Netflix for movies and series. Streaming offers a cheap and legal way to access media and, therefore, may affect both piracy and other legal forms of consuming content. Using aggregate data for 21 countries, as well as detailed time series for the U.S., Aguiar and Waldfogel (2018) suggest that music streams are negatively correlated both with piracy and legal downloads – though the effect on the latter is relatively small, so that streaming likely raises revenues in the music industry.[7]

Access to streaming services also allows users to discover new products, which could boost demand for content through other channels. Datta et al. (2018) investigate the introduction of Spotify by comparing the choices of streaming users (treated) and non-users. They find that streaming increases music consumption, variety of listening choices, and new music discovery.

[7] Relatedly, Hiller (2006) and Kretschmer and Peukert (2020) study the impact of YouTube music video streams on music consumption. The former concludes that YouTube substitutes music sales, while the latter find evidence of complementarity.

Aguiar and Martens (2016) use full clickstream activity data from individual internet users across five E.U. countries and find a positive effect of streaming on licensed sales of digital music, but no significant effects on unlicensed downloads. Aguiar (2017) explores Deezer's introduction of a listening cap on its free services in 2011, based on data from French internet users. He identifies that the move reduced visits to music download sites (official and unofficial), which is consistent with the discovery interpretation.

More related to our contribution, there is an emerging literature on the effects of video streaming. Through a difference-in-differences approach, Lu et al. (2021) and Frick et al. (2023) present evidence that Netflix reduces searches for pirated content. While the former uses Netflix's failure to enter the Indonesian market in 2016 (taking other 41 Asian countries as a control group), the latter explores Epix's decision to withdraw its movies from the platform in 2015 (comparing Epix and non-Epix content).[8] However, in an experiment, Matos et al. (2018) show that BitTorrent users who randomly received a free video streaming package were not more likely to abandon piracy.

The literature points to other margins of substitution associated with video streaming. For instance, Yu et al. (2022) use the same event as Frick et al. to show that Netflix depresses DVD sales. Using state-level data from Brazil, Silva and Lima (2022) conclude that exposure to Netflix (measured by search intensity from Google trends) promotes cord cutting, that is, it leads to a reduction in the number of cable TV subscribers and the exit of small cable providers. Sung (2023) also finds evidence of substitution between Netflix and pay TV in Korea after the COVID-19 outbreak.

[8] Similarly, NBC's temporary removal of its contents from iTunes in 2007-2008 was also accompanied by a rise in piracy, as reported by Danaher et al. (2010).

In principle, we should expect some substitution between streaming and the most traditional way of watching movies – i.e., in movie theaters. First, there is a price advantage: Netflix subscribers pay a fixed amount, which grants access to the service for all members of a given household; a movie ticket only allows one person to watch a movie (see price comparison in Appendix A). Second, the same film can be watched multiple times on Netflix, and the subscriber has access to a vast set of movies, series and documentaries (some of them exclusively through the platform). Third, streaming allows for flexibility both in terms of time and especially place: while in a movie theater the time and venue are somewhat rigid, a film can be streamed on multiple mobile devices (PCs, cellphones, tablets). The user can watch a movie virtually anywhere, provided she has an internet connection (Waldfogel 2017a; Waldfogel 2017b; Clement et al. 2018; Hadida et al. 2018; Kübler et al. 2021).

Nevertheless, the empirical evidence on the effects of streaming on movie consumption in theaters is scarce, and this is the main gap we attempt to fill in the literature. A notable exception is McKenzie et al. (2019), which conducted an experiment with university students in Australia to examine the impact of streaming video on demand on several legal and illegal film media (cinema, free TV, paid TV, rented and bought DVDs, file-sharing websites, among others). They found that such technology is creating disruptions in the alternative film platforms and is highly valued by consumers, supporting our argument that streaming video caused a shock to the previously dominant film media. Our results are thus in line with theirs, but we use actual film consumption data to gauge the effect of streaming on movie theater revenue.

In terms of methodology, our work relates to papers that use a differences-in-differences approach with movie-level data, such as Peukert et al. (2017), Lu et al. (2021), Yu et al. (2022)

and Frick et al. (2023). It is particularly close to Lu et al. (2021). Like in our paper, they use data from the same movies across different countries, with the treatment depending on the country.

3. Data and Empirical Strategy

To address the lack of public information on film consumption from streaming video services, we use the year 2007 as an intervention in the U.S. movie market. The central idea is to use the launch of Netflix streaming video services as a proxy for the introduction of this technology in the U.S. market (Lee 2005). As the incumbent company, Netflix released its video streaming services in 2007 in the U.S. We define our treated group as the U.S., where streaming video services became available earlier for consumers, and our control group as Australia, where Netflix was only launched in 2015.

3.1. Data

The dataset consists of films domestically released in both the U.S. and Australia between 2004 and 2014, with data available at the websites Box Office Mojo and IMDb. We excluded films exhibited in only one country to avoid potential biases due to unobservable characteristics. We focus on widely released films (i.e., exhibited in at least 600 theaters in the U.S. during the opening weekend) since we have more information about them (Leung et al. 2020). We also exclude IMAX movies due to their different exhibition pattern.

We used the Python routine developed by Souza (2021) to collect film data on box office revenues in each country (total accumulated over time and during opening weekend), along with financial and technical characteristics from boxofficemojo.com. These characteristics include month and year of release, number of theaters the film is shown at release in each country, production budget, genre, distributor, and MPAA film indicative classification. Moreover, from imdb.com, we gather information on average film ratings from professional critics and users. Revenues and budgets (all in U.S. dollars) were deflated to 2004 using the U.S. consumer price index from the International Monetary Fund statistics. Appendix B provides further details on the data collection process and reports descriptive statistics for the main variables used in this study.

Given the sample restrictions discussed, we were able to find 950 movies exhibited in both countries with all movie-specific information available. However, for some movies exhibited in Australia, information on the number of theaters was missing. Therefore, our baseline estimations are based on 1,744 observations – 950 for the U.S. market, and 794 for the Australian market.

3.2. Treatment and comparison groups

Our study faces a significant challenge in getting data on U.S. film consumption since domestic box office revenues refer to the North American market, which includes both the U.S. and Canada. Consequently, this could prevent us from having an ideal treatment group given that Netflix was launched in the U.S. in 2007 and Canada in 2010. However, given the lack of an alternative data source that provides such detailed information on film consumption in the U.S., we argue that our exercise is still valid for the following reasons.

First, Canada's population represented only around 11% of that of the U.S. during the period of our study, which suggests that the inclusion of Canadian revenues would have little effect on our results. Second, our results likely *underestimate* the effect of streaming since a portion of the population in the treated group was not exposed to streaming services until 2010. Third, the U.S. and Canada share many similarities, including a common language, a shared colonial past, region and borders, similar cultural preferences, and comparable living standards (Disdier et al. 2009).

For identification and effect evaluation purposes, we have chosen the Australian film market as our control group. This selection is based on data availability and cultural proximity to the treated group, thus allowing more accurate comparisons. Ideally, in our case, the comparison group would be similar to the treated group in terms of cultural goods preferences, which is an unobserved variable. Here, we follow the cultural goods trade literature (Disdier et al. 2009; Holloway 2014) and use language and colonial origin to proxy for these similarities in preferences. Australia fits these criteria. Moreover, the two countries also have comparable living standards: between 2004 and 2019, according to World Bank data, average income per capita was $53,048.78 in the U.S. and $50,571.38 in Australia (2010 constant U.S. dollars). Other countries (like the U.K. and New Zealand) would also be suitable as a control group here, but Australia is the only one whose box office data is not merged with those of other countries.[9]

3.3. Empirical Strategy

We estimate a baseline model as described in equation (1). The dependent variable, R_{ict}, is the log of domestic box office revenues of film *i* in country *c*, and year *t*.

$$R_{ict} = \alpha_0 + \alpha_1 US_c + \alpha_2 S_t + \alpha_3 S_t \times US_c + \Lambda' X_{ict} + u_{ict} \quad (1)$$

where S_t is a binary variable equal to 1 for the years 2007 to 2014 (that is, after Netflix first introduced its streaming services), and 0 otherwise; US_c is equal to 1 if the observation refers to

[9] The U.K. and New Zealand were alternatives regarding the cultural similarity criterium, but film information is not available for these countries in isolation. For instance, U.K. box office information is reported together with Ireland and Malta.

the U.S. market, and 0 if it refers to the Australian market; X_{ict} is a vector of control variables and u_{ict} is the error term. Our main variable of interest is the interaction $S_t \times US_c$, which is equal to 1 only for movies released in the U.S. from 2007 on. These are the movies exposed to the new technology. The coefficient α_3 thus captures the effect of streaming on the log of box office revenues.

The set of covariates X_{ict} encompasses variables that can affect movie consumption at theaters according to the literature (Reinstein and Snyder 2005; Eliashberg et al. 2006; Moon et al. 2010; Moretti 2011; Souza et al. 2019). Specifically, the vector X_{ict} includes critics' and users' ratings to control for film quality; the logarithm of the number of movie screens at which the film is shown on its release weekend to control for advertising; the logarithm of budget to control production costs, including star costs; a dummy for big distributors, that is, those that hold a significant portion of the film production and advertising in the sample;[10] month dummies to control for the seasonality of film releases and advertising spending; year dummies to control for macroeconomic effects, particularly for shocks like the 2008 global financial crisis (GFC) that reduced the countries' income just after the Netflix launch; genre dummies; and dummies of MPAA ratings to control for the film indicative classification.

We also estimate an equation that includes movie fixed effects, as described in equation (2).

$$R_{ict} = \beta_0 + \beta_1 US_c + \beta_2 S_t + \beta_3 S_t \times US_c + \Omega' \tilde{X}_{ict} + \mu_i + v_{ict} \quad (2)$$

where μ_i is the fixed effect for movie i; $\tilde{X}_{ict}$ and v_{ict} are the vector of control variables and the error term, respectively. Notice that here the vector of control variables $\tilde{X}_{ict}$ is different from that

[10] In our definition, big distributors are those that have distributed at least 100 movies between 1986 and 2018.

of equation (1) because it does not include variables that are movie-specific, as they are perfectly collinear with the movie fixed effects. Specifically, $\tilde{X}_{ict}$ encompasses the log of the number of movie screens at release, month dummies and year dummies.

The specification above has the advantage of controlling for unobservable variables that are common to a given movie (for instance, commercial appeal). Nonetheless, since we have at most two observations per film, this strategy is quite demanding in terms of degrees of freedom. The sample size is also smaller in this case (N = 1,588), given that we can use in the estimation only films with complete information for both the U.S. and the Australian market. Therefore, we view these exercises as robustness checks.

Regarding the dependent variable, we estimated our models for the log of box office domestic revenues both aggregated over time and during opening weekend. We report robust standard errors clustered at the genre level.

3.4. Parallel trends

Before turning to our main empirical results, we check for parallel trends between the U.S. and the Australian market during the pre-intervention period – that is, before the launch of Netflix streaming services in the U.S. in 2007 – to establish the validity of our approach. Specifically, we follow Kahn-Lang and Lang (2020) and estimate OLS regressions described by equation (3) below. In particular, we regress the log of box office revenues on the country dummy (US_c), year dummies ($\boldsymbol{y_t}$), and interactions between country and year dummies ($\boldsymbol{y_t} \times US_c$), along with the remaining controls X_{ict}.

$$R_{ict} = a_0 + a_1 US_c + b' \boldsymbol{y_t} \times US_c + c' \boldsymbol{y_t} + d' X_{ict} + e_{ict} \quad (3)$$

Where $\boldsymbol{y_t} = [y_{2005,t}\ y_{2006,t} \dots y_{2014,t}]'$ is a vector of year dummies and e_{ict} is the error term. We omit the 2007 dummy because of perfect collinearity. Figure 2 shows the estimation outcome of equation (3) regarding the coefficients of the interactions $\boldsymbol{y_t} \times US_c$. Results should be read taking the year 2007 (when Netflix was introduced) as reference. The plot on the left-hand side refers to the regression with the log of total revenues as the dependent variable, while the plot on the right-hand side reports results for the log of opening revenues. Each bar shows the point estimate of a given interaction, with a 95% confidence interval.

The insignificance of coefficients prior to 2007 provides favorable evidence that parallel trends hold for our dependent variables. These trends only depart from each other after 2007: coefficients for these years are for the most part negative, which is consistent with a negative effect of Netflix in the U.S. market in comparison with the Australian market.[11]

[11] We also perform these tests with a linear time trend as an additional control, as suggested by Kahn-Lang and Lang (2020). Results (not shown) are qualitatively similar.

Figure 2 – Estimated coefficients of interactions in equation (3)

The figure presents the estimation outputs of equation (3) using a set of movies exhibited in the U.S. and Australia between 2004 and 2014. Two dependent variables are used: the log of overall box office revenues over time (left), and the log of box office revenues during opening weekend (right). The main covariates are year and country dummies, along with a full set of country-year interactions. The bars show the coefficients of these interactions, with a 95% confidence interval (robust standard errors clustered at the genre level). The 2007 dummy and its interaction are omitted because of perfect collinearity. Regressions also include the variables in the vector X_{ict}, that is, critics' ratings, user ratings, log of budget, log of the number of theaters the movie is shown at its release, dummies of big distributors, genre dummies, dummies for MPAA indicative classification, month dummies, and year dummies. Box office and budget data are in constant 2004 U.S. dollars.

4. Results

4.1. Baseline Models

Table 1 shows the estimates of our baseline models. In columns (1) and (2), we estimate the effect of streaming without including fixed effects in the regression (equation (1)). The intervention variable is S_t, which is equal to 1 for the years 2007-2014 (after the introduction of

Netflix streaming services) and zero otherwise. Column (1) shows regression results with the log of overall revenues as the dependent variable, while in column (2) the dependent variable is the log of revenues during opening weekend. We focus on the coefficient of the interaction $S_t \times US_c$.

In both cases, the coefficient is negative and statistically significant at conventional levels, suggesting that streaming contributes to reducing movie theater revenues. Magnitudes are also meaningful. The introduction of streaming is associated with a fall of 15.1 and 18.1 log points in overall and opening revenues, respectively. These correspond to decreases of 14 and 17%. The difference between the coefficients in columns (1) and (2) is not statistically significant (*Prob > chi2 = 0.4296*), indicating a similar loss in overall and opening revenues. In line with McKenzie et al. (2019), these results suggest a substitution pattern from films at theaters to those consumed on streaming video.

Similar conclusions emerge when we add movie fixed effects to the regressions (see columns (3) and (4)). There is some loss of significance, especially in the case of opening revenues. This was expected, given the reduction in degrees of freedom discussed in Section 3.3. Nonetheless, the coefficients of interest remain significant at 10%, with magnitudes comparable to those in columns (1) and (2). In other words, our main results are robust to the inclusion of movie fixed effects.

Table 1
Effect of the streaming intervention on box office revenues (2004-2014)

	Baseline Model		Fixed-effects model	
	(1)	(2)	(3)	(4)
	Dependent Variable		Dependent Variable	
	Log total revenues	Log opening revenues	Log total revenues	Log opening revenues
$S_t \times US_c$	-0.151*	-0.184***	-0.161*	-0.168*
	(0.080)	(0.065)	(0.097)	(0.090)
N	1,744	1,744	1,588	1,588
R-squared	0.876	0.905	0.977	0.981
	Randomization Inference		Randomization Inference	
p-value	0.074	0.011	0.010	0.002

*** p<0.01, ** p<0.05, * p<0.1. Robust standard errors clustered at the genre level in parentheses. The table presents estimation outputs of equations (1) and (2) using a set of movies exhibited in the U.S. and Australia between 2004 and 2014. S_t is equal to 1 for the years 2007 and after, and zero otherwise. Focus is given to the coefficient of the interaction term $S_t \times US_c$. Two dependent variables are used: the log of overall box office revenues over time, and the log of box office revenues during opening weekend. Columns (1) and (2) report estimates of equation (1). These regressions include a U.S. dummy, along with the variables in the vector X_{ict}, that is, critics ratings, user ratings, log of budget, log of the number of theaters the movie is shown at its release, dummy of big distributor, genre dummies, dummies for MPAA indicative classification, month dummies, and year dummies. Columns (3) and (4) report estimates of equation (2). These regressions include a U.S. dummy, movie fixed effects, along with variables in vector $\tilde{X}_{ict}$, that is, log of the number of theaters the movie is shown at its release, month dummies, and year dummies. Box office and budget data are in constant 2004 U.S. dollars. Permutation tests (under "Randomization Inference") were performed following the methodology outlined by Heß (2017), using 500 random draws.

We also estimated models that consider both the treatment described above, as well as an intensity component, measured by the share of the U.S. population with access to Netflix. The coefficient of $S_t \times US_c$ remains negative and significant, with similar magnitude. The intensity component coefficient is however indistinguishable from zero at conventional levels. See discussion in Appendix C.

4.2. Randomization Inference

To lend further credence to our estimates, we implement randomization exercises as outlined by Heß (2017). Specifically, equations (1) and (2) are estimated with a random draw in place of the treatment variable $S_t \times US_c$. This procedure is repeated with several distinct draws, yielding a distribution of coefficients.[12] Our estimated effects of streaming (from Table 1) are then contrasted with this distribution.

The permutation test asks whether our estimates are likely to have come from the constructed distribution of coefficients. The p-values for this test (displayed in Table 1 under "Randomization Inference") are all below 10%, indicating that the effect of Netflix obtained here is unlikely a product of chance. These findings strengthen our evidence of a negative impact of streaming on movie theater consumption shown previously.

4.3. Competing explanations

We now evaluate two alternative explanations for our estimated effects. The first one has to do with the 2008 global financial crisis. Arguably, the rise of economic insecurity would prompt households to cut down consumption (including going to the movies), especially in the U.S., the epicenter of the crisis. In principle, this could account at least partially for the negative effect associated with the introduction of streaming just one year before. To address this issue, we estimated equation (1) by adding the interaction $y_{2008,t} \times US_c$, where $y_{2008,t}$ is a dummy for the year 2008. In this subsection, we focus on regressions without movie fixed effects (baseline).

If the reasoning above is correct, the coefficient of $y_{2008,t} \times US_c$ would be negative. However, in our estimations, it turns out to be positive, although insignificant. See Table 2,

[12] In our case, 500 replications.

columns (1) and (2). On the other hand, the coefficient of our main intervention ($S_t \times US_c$) remains significant and quantitatively relevant in the case of opening revenues. While there is some loss of significance for total revenues, the point estimate magnitude remains meaningful.

Table 2
Alternative explanations

	Global Financial Crisis		Introduction of Netflix original content	
	(1)	(2)	(3)	(4)
	Dependent Variable		Dependent Variable	
	Log total revenues	Log opening revenues	Log total revenues	Log opening revenues
$S_t \times US_c$	-0.115	-0.160**	-0.176**	-0.184***
	(0.091)	(0.070)	(0.082)	(0.067)
$y_{2008,t} \times US_c$	0.059	0.040	–	–
	(0.076)	(0.056)		
$1\{t \geq 2011\} \times US_c$	–	–	0.049	-0.000
			(0.054)	(0.050)
N	1,744	1,744	1,744	1,744
R-squared	0.878	0.906	0.876	0.905

*** p<0.01, ** p<0.05, * p<0.1. Robust standard errors clustered at the genre level in parentheses. S_t is equal to 1 for the years 2007 and after, and zero otherwise. The table presents exercises that consider alternative explanations to our results, based on equation (1). Two dependent variables are used: the log of overall box office revenues over time, and the log of box office revenues during opening weekend. In columns (1) and (2), we evaluate the role of the 2008 global financial crisis as a possible confounder by considering, as an additional control, the interaction between the country dummy and a dummy for the year 2008. The exercises in columns (3) and (4) are similar but consider the first introduction of Netflix original content in 2011 as a second intervention – in this case, the additional covariate is the interaction between the country dummy and a dummy for the post-2011 period. Focus is given the coefficient of our main covariate ($S_t \times US_c$) and that of the additional interaction in each case. Besides these variables, all regressions in the table include a U.S. dummy, along with the variables in the vector X_{ict}, that is, critics ratings, user ratings, log of budget, log of the number of theaters the movie is shown at its release, dummy of big distributor, genre dummies, dummies for MPAA indicative classification, month dummies, and year dummies. Box office and budget data are in constant 2004 U.S. dollars.

We next evaluate the effect of another possible intervention: the first introduction of Netflix's original content. Ever since Netflix began producing and offering original videos on its streaming channel in 2011, there has been much debate about its potential impact on traditional movie theaters (Burroughs 2019; McKenzie et al. 2019). With new and exclusive content unavailable in cinemas, video streaming platforms provide a more differentiated product than previously. This may increase the degree of substitution between watching movies on streaming and in theaters, reducing the time consumers allocate to the latter (Liebowitz and Zentner 2012; Wallsten 2015) as both formats compete for consumer attention and leisure time.

To evaluate this effect, we introduce an additional interaction term in equation (1), namely $1\{t \geq 2011\} \times US_c$, where $1\{t \geq 2011\}$ is a dummy for the years 2011 and after. Results are in Table 2, columns (3) and (4). Once more, for the above argument to hold true, the coefficient of the interaction needs to be negative. But this is the case only in column (4), where the point estimate is tiny. Moreover, in both columns, the coefficients are statistically insignificant.

In other words, we find no robust evidence that the introduction of Netflix's original content has affected box office revenues. By contrast, the coefficient of our main intervention (the launch of Netflix streaming services in 2007) remains significant and even rises in magnitude compared to our baseline estimates (Table 1).

5. Conclusion

This paper examines the impact of video streaming – a modern technological business model that provides diverse access points for video content, such as PCs, mobile devices, and tablets, anywhere with internet connectivity – on box office revenues. We take advantage of the early introduction of Netflix streaming services in the U.S. market (2007) to study its effects on traditional film viewing at theaters. In particular, we use the Australian market as a control group, exploring the fact that Netflix was unavailable in that country until 2015. Using publicly available data from films released in Australia and the U.S. between 2004 and 2014, we find that the launch of Netflix streaming is associated with a decrease of 14 to 17% in box office revenues.

Our results, thus, suggest a significant substitution between streaming and movie consumption at theaters. The literature indicates possible mechanisms behind this effect. One of them involves intertemporal substitution in consumption. A film is usually streamed much later than its release in theaters (Evens et al. 2023). Thus, a group of consumers (typically non-regular moviegoers with greater intertemporal elasticity) may decide to wait until the movie is available on a streaming platform. The difference between the ticket price and the streaming subscription may also play a role in this mechanism (see Appendix Figure A.1 for a comparison).

A second possible mechanism concerns content available on streaming platforms but not in cinemas, such as Netflix original productions (Burroughs 2019; Lobato and Lotz 2020; Shattuc 2019). In this case, streaming may displace the time consumers spend on other types of leisure, including going to movie theaters (Wallsten 2015).

Our results from Section 4.3 seem at odds with the last channel, given the insignificant effects found for the intervention associated with the first introduction of Netflix original content in 2011. However, they are far from definitive and certainly more work is needed to elucidate the mechanisms behind the substitution effect, which we leave for future research.

Finally, it is worth noting that streaming is a new technology that is still growing and expanding globally. Further work will help us to understand the impacts not only of Netflix, but also of other streaming platforms launched more recently, such as HBO Max, Disney+ and Amazon Prime; and not only in the U.S. market but also in other countries. In particular, the inclusion of other countries would provide additional variation in streaming availability dates, thus increasing sample size and allowing a more precise estimation of the effects of this technology.

More importantly, future research should explore other contexts, particularly in developing economies where copyright protection is weaker, and piracy is pervasive. In these settings, the impact of streaming on movie consumption in theaters may be more complex, influencing consumption both directly and indirectly through its effects on piracy.

References

Aguiar, L. (2017). Let the music play? Free streaming and its effects on digital music consumption. *Information Economics and Policy*, 41: 1–14. https://doi.org/10.1016/j.infoecopol.2017.06.002

Aguiar, L., Martens, B. (2016). Digital music consumption on the internet: Evidence from clickstream data. *Information Economics and Policy*, 34: 27–43.

Aguiar, L., Waldfogel, J. (2018). As streaming reaches flood stage, does it stimulate or depress music sales? *International Journal of Industrial Organization*, 57: 278–307. http://doi.org/10.1016/j.ijindorg.2017.06.004

Burroughs, B. (2019). House of Netflix: Streaming media and digital lore. *Popular Communication*, 17(1): 1–17. doi: https://doi.org/10.1080/15405702.2017.1343948

Clement, M., Otten, C., Seifert, R., Kleinen, O., Houston, M. B., Karniouchina, E. V., Heller, C. (2018). IDEA FORUM: The Impact of Subscription-Based Video on Demand on Traditional Distributors' Value Chains and Business Models. *Journal of Media Economics* 31: 50–67. https://doi.org/10.1080/08997764.2020.1796687

Chen, H., Hu, Y. J., Smith, M. D. (2019). The Impact of E-Book Distribution on Print Sales: Analysis of a Natural Experiment. *Management Science* 65(1): 19–31. https://doi.org/10.1287/mnsc.2017.2940

Danaher, B., Dhanasobhon, S., Smith, M. D., Telang, R. (2010). Converting pirates without cannibalizing purchasers: The impact of digital distribution on physical sales and internet piracy. *Marketing Science*, 29(6): 963–1169. https://doi.org/10.1287/mksc.1100.0600

Danaher, B., Waldfogel, J. (2012). Reel Piracy: The Effect of Online Film Piracy on International Box Office Sales. SSRN Scholarly Paper. Rochester, NY, January 16, 2012. https://doi.org/10.2139/ssrn.1986299

Datta, H., Knox, G., Bronnenberg, B. J. (2018). Changing Their Tune: How Consumers' Adoption of Online Streaming Affects Music Consumption and Discovery. *Marketing Science*, 37(1): 16–136. https://doi.org/10.1287/mksc.2017.1051

De Vany, A. S., Walls, W. D. (2007). Estimating the Effects of Movie Piracy on Box-Office Revenue. *Review of Industrial Organization*, 30(4): 291–301. https://doi.org/10.1007/s11151-007-9141-0

Deleersnyder, B., Geyskens, I., Gielens, K., Dekimpe M. G. (2002). How Cannibalistic Is the Internet Channel? A Study of the Newspaper Industry in the United Kingdom and The Netherlands. *International Journal of Research in Marketing*, 19(4): 337–48. https://doi.org/10.1016/S0167-8116(02)00099-X

Disdier, A. C.; Tai, S. H. T.; Fontagné, L.; Mayer, T. (2009). Bilateral Trade of Cultural Goods. *Review of World Economics*, 145(4): 575–595. doi: https://doi.org/10.1007/s10290-009-0030-5.

Eliashberg, J.; Elberse, A.; Leenders, M. A. A. M. (2006). The Motion Picture Industry: Critical Issues in Practice, Current Research, and New Research Directions. *Marketing Science*, 25(6), 638–61.

Evens, T., Henderickx, A., Conradie, P. (2023). Technological affordances of video streaming platforms: Why people prefer video streaming platforms over television. *European Journal of Communication*, 02673231231155731.

Frick, S. J., Fletcher, D., Smith, A. C. (2023). Pirate and Chill: The Effect of Netflix on Illegal Streaming. *Journal of Economic Behavior and Organization*, 209: 334–47. https://doi.org/10.1016/j.jebo.2023.03.013

Gentzkow, M. (2007). Valuing new goods in a model with complementarity: Online newspapers. *American Economic Review*, 97(3): 713–744. https://doi.org/10.1257/aer.97.3.713.

Hadida, A. L., Lampel, J., Walls, W. D., Joshi, A. (2020). Hollywood studio filmmaking in the age of Netflix: a tale of two institutional logics. *Journal of Cultural Economics*, 45: 213-238. https://doi.org/10.1007/s10824-020-09379-z.

Heß, S. (2017). Randomization Inference with Stata: A Guide and Software. *Stata Journal*, 17(3): 630-651. https://doi.org/10.1177/1536867X1701700306

Hiller, S. R. (2016). Sales Displacement and Streaming Music: Evidence from YouTube. *Information Economics and Policy*, 34: 16–26. https://doi.org/10.1016/j.infoecopol.2015.12.002

Holloway, I. R. (2014). Foreign entry, quality, and cultural distance: product-level evidence from US movie exports. *Review of World Economics*, 150(2): 371–392. https://doi.org/10.1007/s10290-013-0180-3.

Kahn-Lang, A., Lang, K. (2020). The Promise and Pitfalls of Differences-in-Differences: Reflections on 16 and Pregnant and Other Applications. *Journal of Business and Economic Statistics*, 38(3): 613–620. http://doi.org/10.1080/07350015.2018.1546591.

Kim, E.; Kim, S. (2017). Online movie success in sequential markets: Determinants of video-on-demand film success in Korea. *Telematics and Informatics*, 34: 987–995. https://doi.org/10.1016/j.tele.2017.04.009.

Kretschmer, T., Peukert, C. (2020). Video Killed the Radio Star? Online Music Videos and Recorded Music Sales. *Information Systems Research*, 31(3): 776–800. https://doi.org/10.1287/isre.2019.0915

Kübler, R., Seifert, R., Kandziora, M. (2021). Content Valuation Strategies for Digital Subscription Platforms. *Journal of Cultural Economics* 45(2): 295–326. https://doi.org/10.1007/s10824-020-09391-3

Lee, M.-J. (2005). Micro-Econometrics for Policy, Program, and Treatment Effects. *Advanced Texts in Econometrics*. Oxford.

Leung, T. C., Qi, S., Yuan, J. (2020). Movie Industry Demand and Theater Availability. *Review of Industrial Organization*, 56: 489–513. https://doi.org/10.1007/s11151-019-09706-5.

Liebowitz, S., Zentner, A. (2012). Clash of the Titans: Does Internet use reduce television viewing? *Review of Economics and Statistics*, 94(1): 234–245.

Liebowitz, S. J. (2016). How Much of the Decline in Sound Recording Sales Is Due to File-Sharing? *Journal of Cultural Economics*, 40(1): 13–28.

Lobato, R., Lotz, A. D. (2020). Imagining Global Video: The Challenge of Netflix. *JCMS: Journal of Cinema and Media Studies*, 59(3): 132–136. https://doi.org/10.1353/cj.2020.0034.

Lu, S., Rajavi, K., Dinner, I. (2021). The Effect of Over-the-Top Media Services on Piracy Search: Evidence from a Natural Experiment. *Marketing Science*, 40(3): 548–68. https://doi.org/10.1287/mksc.2020.1256

Ma, L., Montgomery, A. L., Singh, P. V., Smith, M. D. (2014). An Empirical Analysis of the Impact of Pre-Release Movie Piracy on Box Office Revenue. *Information Systems Research*, 25(3): 590–603.

Ma, L., Montgomery, A., Smith, M. D. (2016). The Dual Impact of Movie Piracy on Box-Office Revenue: Cannibalization and Promotion. SSRN Scholarly Paper. Rochester, NY, February 24, 2016. https://doi.org/10.2139/ssrn.2736946

Matos, M. G. de, Ferreira, P., Smith, M. D. (2018). The effect of subscription video-on-demand on piracy: evidence from a household-level randomized experiment. *Management Science*, 64(12): 5610–5630. https://doi.org/10.1287/mnsc.2017.2875.

McKenzie, J. (2023). The Economics of Movies (Revisited): A Survey of Recent Literature." *Journal of Economic Surveys*, 37(2): 480–525. https://doi.org/10.1111/joes.12498

McKenzie, J., Crosby, P., Cox, J., Collins, A. (2019). Experimental evidence on demand for 'on-demand' entertainment. *Journal of Economic Behavior and Organization*, 161: 98–113. https://doi.org/10.1016/j.jebo.2019.03.017.

McKenzie, J., Crosby, P., Shin, S. Y. (2023). Netflix Chills and Revamps Its Viewing Metrics: Preliminary Analysis and Opportunities for Research. *Poetics*, 96: 101738. https://doi.org/10.1016/j.poetic.2022.101738

Moon, S., Bergey, P. K., Iacobucci, D. (2010). Dynamic Effects among Movie Ratings, Movie Revenues, and Viewer Satisfaction. *Journal of Marketing*, 74(1), 108–121. https://doi.org/10.1509/jmkg.74.1.108

Moretti, E. (2011). Social Learning and Peer Effects in Consumption: Evidence from Movie Sales. *Review of Economic Studies*, 78(1), 356-393.

Oberholzer-Gee, F., Strumpf, K. (2007). The Effect of File Sharing on Record Sales: An Empirical Analysis. *Journal of Political Economy*, 115(1): 1–42. https://doi.org/10.1086/511995

Peukert, C., Claussen, J., Kretschmer, T. (2017). Piracy and Box Office Movie Revenues: Evidence from Megaupload. *International Journal of Industrial Organization*, 52: 188–215. https://doi.org/10.1016/j.ijindorg.2016.12.006

Reinstein, D. A., Snyder, C. M. (2005). The influence of expert reviews on consumer demand for experience goods: A case study of movie critics. *Journal of Industrial Economics*, 53(1): 27–51. https://doi.org/10.1111/j.0022-1821.2005.00244.x.

Rob, R., Waldfogel, J. (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. https://doi.org/10.1086/430809

Rob, R., Waldfogel, J. (2007). Piracy on the Silver Screen. *Journal of Industrial Economics*, 55(3): 379–395. http://doi.org/10.1111/j.1467-6451.2007.00316.x.

Shattuc, J. (2019). Netflix, Inc. and Online Television. *A Companion to Television*, 145–164. https://doi.org/10.1002/9781119269465.ch7

Silva, J. M. S., Lima, R. C. A. (2022). Is Netflix a Threat to the Cable TV Industry? Evidence from Brazil. *Telecommunications Policy*, 46(3): 102274. https://doi.org/10.1016/j.telpol.2021.102274

Souza, G. D. (2021). *Os efeitos de streaming de vídeo sobre o mercado de cinema dos Estados Unidos*. Dissertação de Mestrado, Escola de Artes, Ciências e Humanidades, Universidade de São Paulo, São Paulo. https://doi:10.11606/D.100.2021.tde-11112021-153414.

Souza, T. L. D., Nishijima, M., Fava, A. C. P. (2019). Do consumer and expert reviews affect the length of time a film is kept on screens in the USA? *Journal of Cultural Economics*, 43: 145–171. https://doi.org/10.1007/s10824-018-9332-6.

Sung, N. (2023). COVID-19, over-the-top services, and the future of pay television: the case of South Korea. *Applied Economics*, 56(26): 3063–3077.

Varian, H. R. (2005). Copying and Copyright. *Journal of Economic Perspectives*, 19(2): 121–138. https://doi.org/10.1257/0895330054048768.

Waldfogel, J. (2010). Music File Sharing and Sales Displacement in the iTunes Era. *Information Economics and Policy*, 22(4): 306–14. https://doi.org/10.1016/j.infoecopol.2010.02.002

Waldfogel, J. (2017a). Cinematic Explosion: New Products, Unpredictability and Realized Quality in the Digital Era. *The Journal of Industrial Economics*. 64(4): 755–772. https://doi.org/10.1111/joie.12117.

Waldfogel, J. (2017b). How digitization has created a golden age of music, movies, books, and television. *Journal of Economic Perspectives*, 31(3): 195–214. https://doi.org/10.1257/jep.31.3.195.

Wallsten, S. (2015). What Are We Not Doing When We Are Online? In Goldfarb, A; Greenstein, S.M.; Tucker, C.E. *Economic Analysis of the Digital Economy*. University of Chicago Press, pages 55–82. https://doi.10.7208/chicago/9780226206981.003.0002

Yu, Y., Chen, H., Peng, C., Chau, P. Y. K. (2022). The Causal Effect of Subscription Video Streaming on DVD Sales: Evidence from a Natural Experiment. *Decision Support Systems*, 157: 113767. https://doi.org/10.1016/j.dss.2022.113767

Yue, Y. (2020). The Effects of Movie Piracy on Box-Office Revenue: An Empirical Analysis of the Chinese Movie Market. *Journal of Applied Economics*, 23(1): 618–55. https://doi.org/10.1080/15140326.2020.1812477

Zentner, A. (2006). Measuring the Effect of File Sharing on Music Purchases. *Journal of Law and Economics*, 49(1): 63–90. https://doi.org/10.1086/501082

Compliance with Ethical Standards

Funding: This study was funded by the Coordination for the Improvement of Higher Education Personnel, CAPES scholarship and also by the National Council for Scientific and Technological Development, CNPq, scholarship. Mauro Rodrigues acknowledges financial support from CAPES and Fundação Instituto de Pesquisas Econômicas (Fipe).

Conflict of Interest: The authors have no conflict of interest to disclose.

Appendices for "Is video streaming hurting box office revenues at U.S. theaters?"

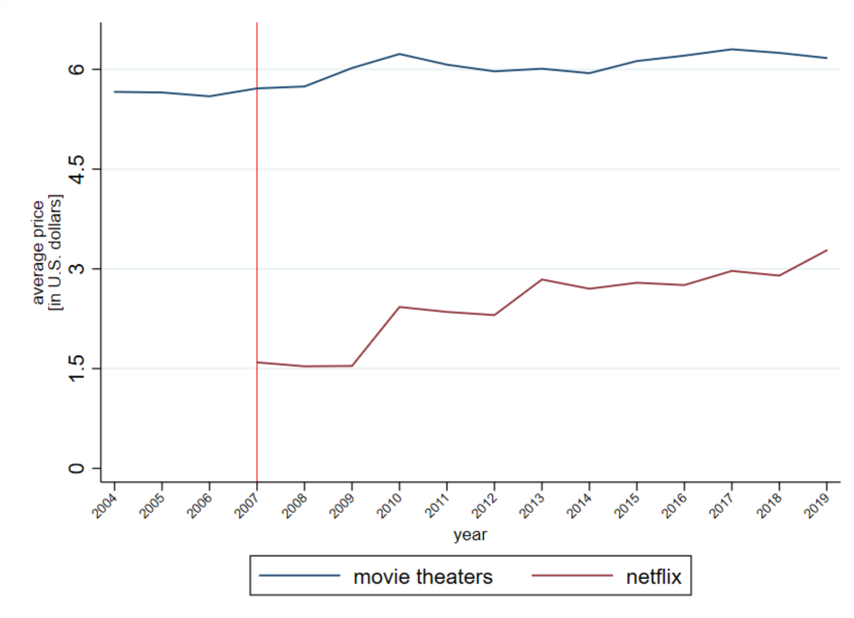
Corresponding author: Gabriela Duarte de Souza
School of Arts, Sciences and Humanities - University of Sao Paulo
gabriela-duarte@usp.br, ORCID: 0000-0003-0495-1324

Marislei Nishijima
Institute of International Relations - University of Sao Paulo
marislei@usp.br, ORCID: 0000-0003-1162-7987

Mauro Rodrigues
Department of Economics - University of Sao Paulo
mrodrigues@usp.br, ORCID: 0000-0003-3745-3989

Appendix A – Price comparison between movie ticket and Netflix subscription

Figure A.1 shows the U.S. average prices of a movie ticket and a Netflix monthly subscription (per person) between 2004 and 2014. The data is from Statista. From the 2020 U.S. Census, the average number of persons in a household is 2.6. We suppose that a subscription gives access to streaming for all members of a given household. Therefore, the values for Netflix shown in the figure are subscription prices divided by 2.6. Values are in constant 2004 U.S. dollars. Although both prices are increasing, the price of a Netflix subscription remains below that of a movie ticket throughout the whole period. It is important to notice that a ticket allows an individual to see only one movie, while the streaming subscription enables watching videos all month long.



Source: Statista website

Figure A.1
Average U.S. prices of a movie ticket and a monthly Netflix subscription (per person), constant 2004 U.S. dollars

Appendix B – Data

We use the Python code developed by Souza (2021) to collect movie-specific public information from the specialized websites boxofficemojo.com and imdb.com.[1] On these websites, each film has a specific page with detailed information. Figure B.1 displays an example, with screenshots from boxofficemojo.com regarding the movie *The Avengers* (2012). The image on the top panel brings information from the U.S. market.

The algorithm scrapes this page, collecting information on box office revenues (overall and during the opening weekend), release date, number of theaters at release, budget, genre, distributor and MPAA rating. The image on the bottom panel shows the same page but for the Australian

[1] The procedures used here are simple and did not require heavy computational capabilities. They were implemented in a standard laptop (Intel Core i7, CPU @2.80 GHz, RAM 16.0 GB). Within Python, we used the library Scrapy (https://github.com/scrapy/scrapy) to collect the data from the web.

market, from where we scrap data on box office revenues, release date and number of theaters. We complement our data set with information from users' and critics' ratings, which we get from imdb.com. Figure B.2 displays a screenshot, again for *The Avengers*. The algorithm scrapes the information indicated by a red arrow – in this case 8,0/10 for users, and 69/100 for critics (Metascore). We normalize these values, so they are on a 0-1 scale.

This procedure is repeated automatically for all movies in our sample, producing a .txt file that can be uploaded to specialized statistical software (in our case, Stata) to implement our regression exercises.[2] In addition, we append to our dataset information on the U.S. Consumer Price Index (from the IMF statistics webpage) to deflate monetary values. Table B.1 provides descriptive statistics and data sources for the key variables used in our regressions.

[2] Within Stata, the commands to run regressions are standard and built-in. The only exception is the randomization inference exercise (Section 4.2), for which we used the ritest command written by Heß (2017). See https://github.com/simonheb/ritest

United States

Title Summary | Original Release | Domestic

Grosses		
DOMESTIC (41%) $623,357,910 INTERNATIONAL (59%) $895,455,078 WORLDWIDE $1,518,812,988	Distributor	Walt Disney Studios Motion Pictures See full company information
	Opening	$207,438,708 4.349 theaters
	Budget	$220,000,000
	Release Date	04/05/2012 - 04/10/2012
	MPAA	PG-13
	Running Time	2 hr 23 min
	Genres	Action Sci-Fi
	In Release	242 days/34 weeks
	Widest Release	4.349 theaters
	IMDbPro	See more details at IMDbPro

Australia

Title Summary | Original Release | Australia

Grosses		
AUSTRALIA $54,385,465 DOMESTIC (41%) $623,357,910 WORLDWIDE $1,518,812,988	Distributor	Walt Disney Pictures See full company information
	Opening	$13,923,182 621 theaters
	Budget	$220,000,000
	Release Date	25/04/2012
	MPAA	PG-13
	Running Time	2 hr 23 min
	Genres	Action Sci-Fi
	In Release	251 days/35 weeks
	Widest Release	627 theaters
	IMDbPro	See more details at IMDbPro

Figure B.1 – Screenshots from boxofficemojo.com for the movie *The Avengers* (2012)

Sources: https://www.boxofficemojo.com/release/rl709199361/ (United States),

https://www.boxofficemojo.com/release/rl959612417/weekend/ (Australia)

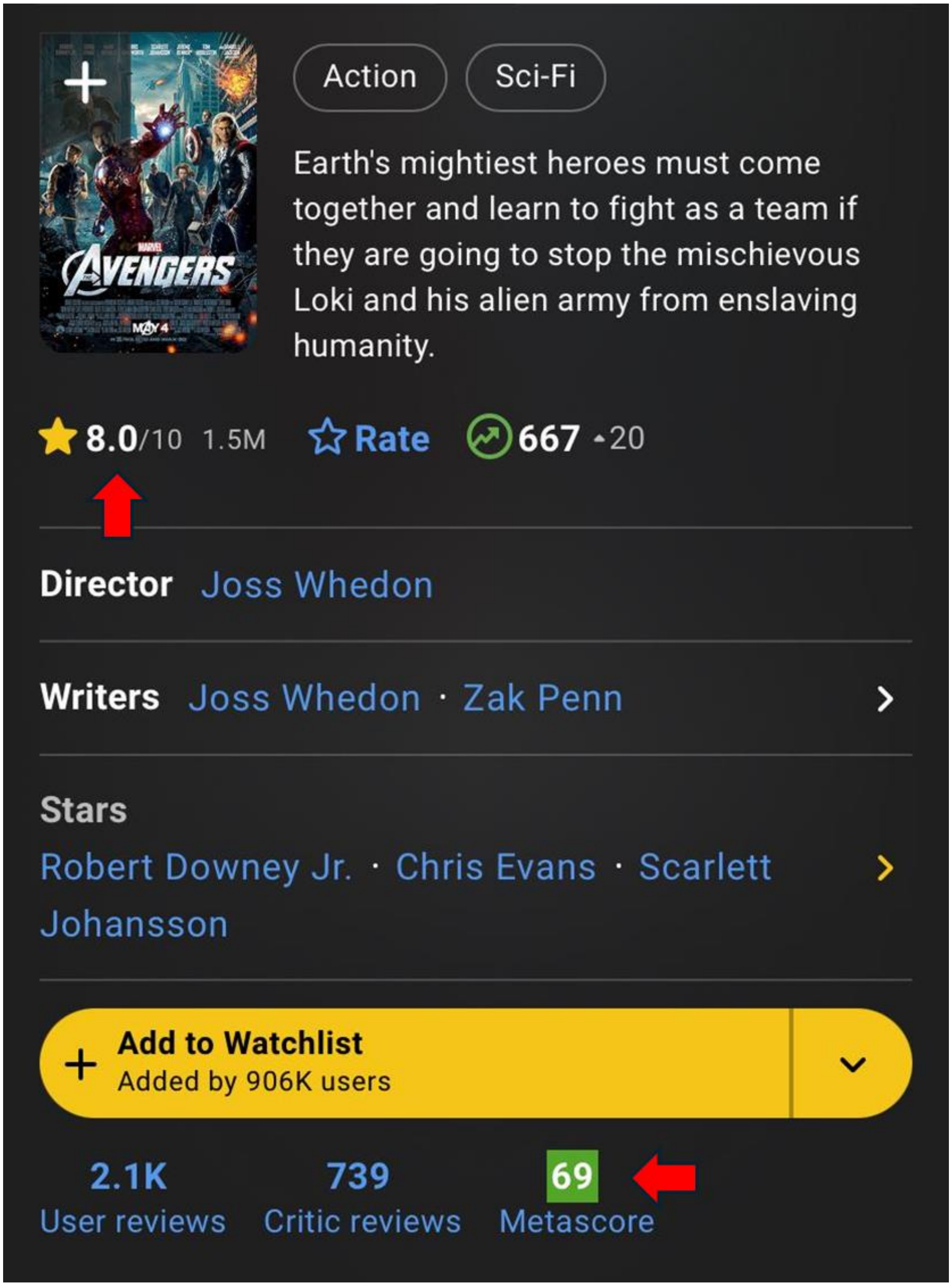


Figure B.2 – Screenshot from imdb.com for the movie *The Avengers* (2012)

Source: https://www.imdb.com/title/tt0848228/

Table B.1 – Descriptive Statistics

Variable	Obs.	Mean	Std. Dev.	Min	Max	Source
Logarithm of domestic film revenues (constant 2014 dollars)	1,744	16.41	1.78	7.08	20.23	Box Office Mojo
Logarithm of film opening revenues (constante 2014 dollars)	1,744	15.25	1.76	7.08	18.86	Box Office Mojo
Intervention dummy (S_t), 1 if year ≥ 2007, 0 o/w	1,744	0.77	0.42	0	1	-
U.S. dummy	1,744	0.54	0.50	0	1	Box Office Mojo
Critics' ratings (0-1 scale)	1,744	0.52	0.16	0.11	0.96	IMDb
User ratings (0-1 scale)	1,744	0.64	0.09	0.16	0.90	IMDb
Logarithm of budget (constant 2014 dollars)	1,744	17.42	0.91	13.53	19.33	Box Office Mojo
Logarithm of the number of theaters at release	1,744	6.78	1.41	0.69	8.40	Box Office Mojo
Big distributor, 1 if the distributor has more than 100 movies in the sample; 0 o/w	1,744	0.67	0.47	0	1	Box Office Mojo
Dummies of Month of film release	1,744	-	-	1	12	Box Office Mojo
Dummies of Year of film release	1,744	-	-	2004	2014	Box Office Mojo
Dummies of Genre	1,744	-	-			Box Office Mojo
Dummies of MPAA film indicative classification	1,744	-	-			Box Office Mojo

Monetary values are deflated using the U.S. consumer price index.

Appendix C – Intensity treatment

Here we estimate a version of equations (1) and (2) that considers an intensity component to the treatment. This intensity component is based on the share of the U.S. population exposed to Netflix streaming services, which is obtained as follows. We assume that each subscription allows all members of a given household to have access to the service, and that there are 2.6 persons per household (average across U.S. households according to the 2020 Census). Then, for $t \geq 2007$, the estimated share of the U.S. population with access to Netflix streaming, which we denote θ_t, is:

$$\theta_t = \frac{2.6 \times \text{Number of Netflix subscriptions}_t}{\text{U.S. Population}_t}$$

Where the number of subscriptions is the same as in Figure 1; additionally, $\theta_t = 0$ for $t < 2007$. For the model without movie fixed effects, the intensity specification is therefore:

$$R_{ict} = \alpha_0 + \alpha_1 US_c + \alpha_2 \theta_t + \alpha_3 \theta_t \times US_c + \Lambda' X_{ict} + u_{ict} \quad (1')$$

For the model with movie fixed effects, we have:

$$R_{ict} = \beta_0 + \beta_1 US_c + \beta_2 \theta_t + \beta_3 \theta_t \times US_c + \Omega' \tilde{X}_{ict} + \mu_i + v_{ict} \quad (2')$$

Table C.1 shows regression outputs. We focus on the coefficient of the interaction $\theta_t \times US_c$. Columns (1) and (2) display estimates of equation (1'). Although negative, the estimated effect is statistically insignificant for both total film revenues and opening revenues.

We next consider simultaneously in the regression both our main treatment (S_t) and the intensity treatment. The idea is to understand how the introduction of Netflix (given by S_t) and its expansion (given by θ_t) affect box office performance. We do this by adding S_t and $S_t \times US_c$ as covariates in regression (1'). Results are in columns (3) and (4). While the intensity component remains statistically indistinguishable from zero, the effect of the introduction of Netflix is still significant, and its magnitude rises in comparison to estimates in Table 1.

Table C.1
Estimations with intensity component

	Baseline Model				Fixed-effects Model			
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
	Dependent Variable		Dependent Variable		Dependent Variable		Dependent Variable	
	Log total revenues	Log opening revenues	Log total revenues	Log opening revenues	Log total revenues	Log opening revenues	Log total revenues	Log opening revenues
$\theta_t \times US_c$	-0.157	-0.295	0.394	0.292	-0.152	-0.324	0.365	0.100
	(0.298)	(0.251)	(0.341)	(0.306)	(0.374)	(0.339)	(0.442)	(0.402)
$S_t \times US_c$			-0.222**	-0.237***			-0.226*	-0.185*
			(0.094)	(0.081)			(0.117)	(0.109)
N	1,744	1,744	1,744	1,744	1,588	1,588	1,588	1,588
R-squared	0.876	0.905	0.877	0.905	0.977	0.981	0.977	0.981

*** p<0.01, ** p<0.05, * p<0.1. Robust standard errors clustered at the genre level in parentheses. The table presents estimation outputs of equations (1’) and (2’) using a set of movies exhibited in the U.S. and Australia between 2004 and 2014. Focus is given to the coefficients of the interaction terms $S_t \times US_c$ and $\theta_t \times US_c$. Two dependent variables are used: the log of overall box office revenues over time, and the log of box office revenues during opening weekend. Columns (1) and (2) report estimates of equation (1). Columns (3) and (4) include the interaction $S_t \times US_c$ to the regression. These regressions include a U.S. dummy, along with the variables in the vector X_{ict}, that is, critics ratings, user ratings, log of budget, log of the number of theaters the movie is shown at its release, dummy of big distributor, genre dummies, dummies for MPAA indicative classification, month dummies, and year dummies. Columns (5)-(8) are analogous to (1)-(4), but report estimates of equation (2’). These regressions include a U.S. dummy, movie fixed effects, along with variables in vector $\tilde{X}_{ict}$, that is, log of the number of theaters the movie is shown at its release, month dummies, and year dummies. Box office and budget data are in constant 2004 U.S. dollars.

In columns (5)-(8), we repeat these exercises for the specifications with movie fixed effects (equation (2’)). Results are broadly the same. In other words, the negative effect of Netflix on box office revenues seems to be driven by its introduction, but not by its expansion.

References

Heß, S. (2017). Randomization Inference with Stata: A Guide and Software. *Stata Journal*, 17(3): 630-651. https://doi.org/10.1177/1536867X1701700306

Souza, G. D. (2021). *Os efeitos de streaming de vídeo sobre o mercado de cinema dos Estados Unidos*. Dissertação de Mestrado, Escola de Artes, Ciências e Humanidades, Universidade de São Paulo, São Paulo. https://doi:10.11606/D.100.2021.tde-11112021-153414.