Online Appendix

A Theoretical background and supporting evidence

Theoretical background. We provide a very simple model to show how the implementation of HADOPI can lead to more admissions for American movies but fewer admissions for French movies, the overall effect being a total demand in theaters that remains constant.

We assume, that consumers have two units of time: one unit of time to consume online contents like a pirated version of a movie or a series and one unit of time to consume a movie in theaters. We abstract from the pricing of such contents because theaters practice uniform pricing for all movies. These units of time reflects the fact that consumers are budget or time constrained, or that they aim at a level of expenditure (in time or money) in a given category of product (Thaler (1985), and Heath and Soll (1996)).

For simplicity, we assume that the utility for consumer i in linear: $U_i = x_{i,j} + y_{i,k}$ where x is the utility that consumer i derives from the offline product j and y the utility derived from the online product k. For the offline product, the consumers must choose between a French movie which generates a random utility $x_{i,F}$ with cdf $F(.)$ in $[0, \overline{x}]$ and an American movie which generates a random utility $x_{i,A}$ with cdf $F(.)$ in $[0, \overline{x}]$. Before the anti-piracy law, a consumer can choose between the pirated version of the American movie which generates an utility $\alpha x_{i,A}$ with $\alpha < 1$ because of the quality degradation from consuming a non genuine version of the movie, and another type of content which generates an utility $x_{i,O}$ with cdf $F(.)$ in $[0, \overline{x}]$. We further assume that an individual will not consume offline a movie he has already watched online via a pirated copy. This assumption seems quite reasonable in the context of the movie industry, as most people only watch a movie once.

Before HADOPI, the market share of French s_F and American movies s_A in theaters are the followings:

$$s_F = Prob[x_{i,F} > x_{i,A} \,\&\, x_{i,O} > \alpha x_{i,A}] + Prob[x_{i,O} \leq \alpha x_{i,A}]$$
$$s_A = Prob[x_{i,F} < x_{i,A} \,\&\, x_{i,O} > \alpha x_{i,A}]$$

It is easy to see that $s_A + s_F = 1$ and $s_F > s_A$.

After the anti-piracy law, consumers cannot choose anymore to see the pirated version of the American movie online so that all them choose the other type of online content. The market share of French and

American movies in theaters are now the followings:

$$\hat{s}_F = Prob[x_{i,F} > x_{i,A}] = 1/2$$
$$\hat{s}_A = Prob[x_{i,F} < x_{i,A}] = 1/2$$

with $\hat{s}_F + \hat{s}_A = 1$, $\hat{s}_F < s_F$, and $\hat{s}_A < s_A$.

In this very simple model, the total demand remains unchanged before and after the adoption of the anti-piracy law, and there is a redistribution effect at the expense of French movies after the law because American movies do not suffer anymore from a substitution effect with the online pirated version.

A business stealing effect is plausible. We provides contextual data supporting the mechanism leading to this substitution effect, namely that the average expense of moviegoers in theaters is stable over time, and that an important share of consumers enjoy watching both American and French movies in theaters. We also shows that consumers tend to prefer American movies, which strengthens this mechanism.

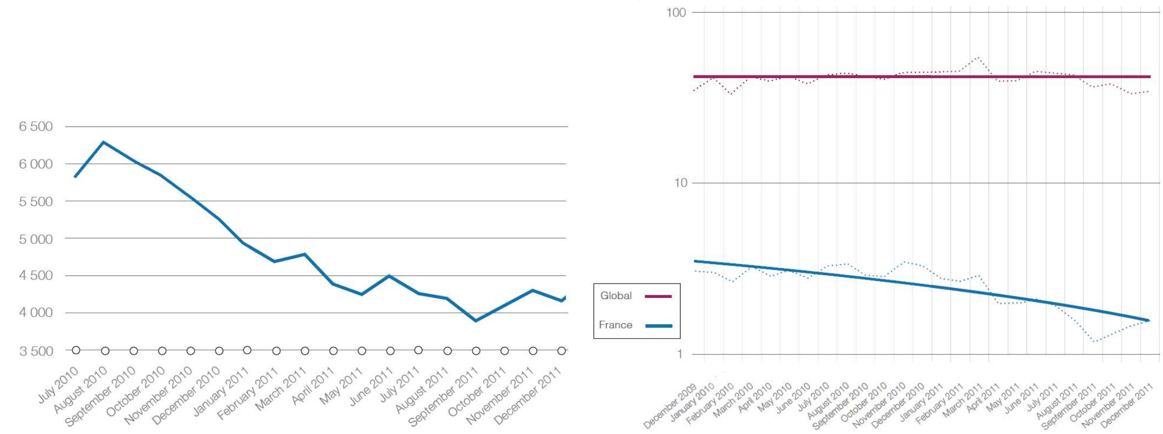
The results of this paper indicate that the increase in American market share mainly stems from cannibalization at the expense of other movies. Indeed, over the period 2008-2011, the aggregate market share of American movies was 46% (48%) before (after) the law was passed, while for French ones, it was 42% (38%) before (after) the law was passed. The mechanism involves a decrease in illegal sharing of movies, a binding budget and time constraint, some consumers enjoying both U.S. and French movies, and a general preference for U.S. movies.

The law has presumably decreased the level of online piracy for several reasons. First, many sources tend to show that there was a decline in peer-to-peer use from September 2010 to December 2011, when the graduated response started being implemented in France.[28] Nielsen noted an important reduction of 50% in the audience levels of websites offering links (see graph 4(a)), whereas Peer Media also measured a drop of 43% in the illegal sharing of films on peer-to-peer networks in France during 2011 (see graph 4(b)).[29] This decline is consistent with the considerable number of messages sent by the HADOPI agency. Moreover, in a survey conducted in 2011 (Hadopi (2011)), 72% of warned Internet users reported that they had reduced or completely stopped their illegal usage following this warning.

Mediametrie/NetRatings report a stability in usage patterns of streaming and direct download services in 2010 and 2011 (see graph 5). Although the HADOPI law was adopted at the end of 2009, it is worth reminding that this law came into force during the last third of 2010, which validates in part the comparison

28. Unfortunately, comparable figures for the period preceding the HADOPI law are not available.
29. Peer Media is an American company providing anti-piracy services targeted at peer-to-peer networks.

Figure 4 – A clear decline in illegal downloading in France
(Sources: (a) IFPI / Nielsen, "Digital Music Report 2012", January 2012, total duplicated audience offering links to P2P files and applications, across approximately 40 P2P services, in thousand of unique visitors. (b) Peer Media Technologies, February 2012, sharing of internationally-observed films, change between December 2009 and December 2011, in millions of downloads initiated. Sample of 200 to 300 recent films in rotation.)



(a) The fall in audience levels of websites offering links to peer-to-peer files and applications

(b) The drop in illegal sharing of movies on peer-to-peer networks in France compared to the rest of the world

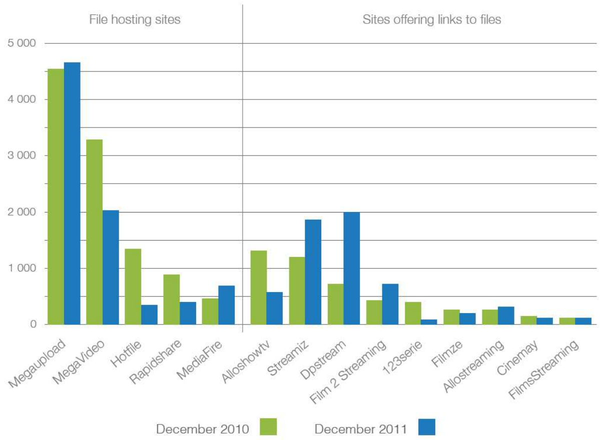
between (end of) years 2010 and 2011. Darmon et al. (2016) show using a survey of 2000 individuals conducted in 2012 that 78% of Internet users rightly believed that the HADOPI agency monitored illegal peer-to-peer downloads, but 68% (respectively 37% and 12%) of them also thought that the HADOPI monitored illegal direct downloads (respectively illegal streaming and illegal offline file sharing) while this is not the case. This body of evidence converges to show a decrease in online piracy that has mainly come from peer-to-peer channels and without important transfers to other piracy channels.

Data from the French national accounts on household consumption show that the share of consumption of movies in theaters in the shopping basket of the average French household has been stable since 1990 (see graph 6(a)). Data from the CNC also show that the average number of admissions per moviegoers is stable since 1998 (see graph 6(b)). This supports the view that budget and time constraints might constitute important limitations to the expansion of the market for theatrical exhibition, or that individuals set monetary or time budgets for categories of expenses (Heath and Soll (1996)).

Next, a survey conducted by *Observatoire de la satisfaction* shows that the distribution of audiences for American and French movies overlap significantly in terms of gender, age, and satisfaction rate (see graphs 7(a), 7(b), and 7(c)).[30] They use a sample of 598 movies widely released in France between January

30. *Observatoire de la satisfaction* is an independent research and polling institute specialized in the movie industry.

Figure 5 – The stability in usage patterns of streaming and direct download services in France. (Source: Mediametrie/NetRatings.)



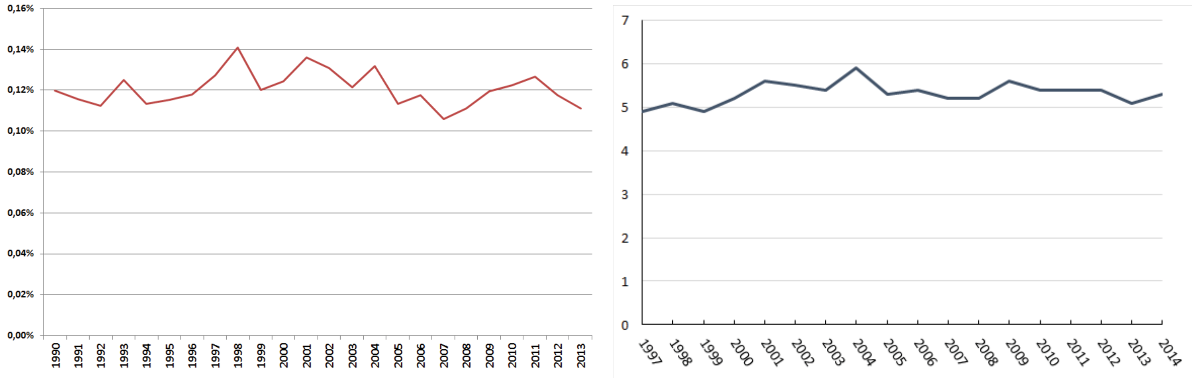
of 2006 and November of 2009. Thus, many consumers are likely to enjoy both French and U.S. movies.

Finally, several evidence show that many French consumers tend to prefer American movies to French ones, which is a necessary condition to obtain a business stealing effect (the production budget, marketing expenditures, number of screens during the release week, and consumer ratings are significantly higher for American movies than for French ones. Indeed, the average production budget is tremendously higher for U.S. movies ($63 millions) than for French ones ($9 millions). This difference reflects for instance a more famous casting or better special effects associated. The audience may also anticipate that U.S. films are superior because marketing expenditures are also higher ($2 millions for U.S. movies against $1.1 millions for French ones). The observed ex post satisfaction of consumers is higher for U.S. movies. Indeed, the average user rating on www.allocine.fr, the major French content aggregator on movies (www.allocine.fr), is 3.1 for U.S. films when it is 2.8 for French films. Finally, during their release week, U.S. movies are played on 360 screens on average in France when French movies are played on 320 screens. Note that these figures correspond to the sample we use in section 4, that is biased toward big French movies. For instance, French movies are released on 180 screens on average in France, when considering all movies.

B Details on the Internet data for analysis 1

In France, there are 33 millions local loops, also called connections, that can provide Internet to households, distributed over 15 000 Internet local exchanges. Even if all local exchanges can provide DSL technology, not all connections qualify for broadband Internet. The download speed of an Internet

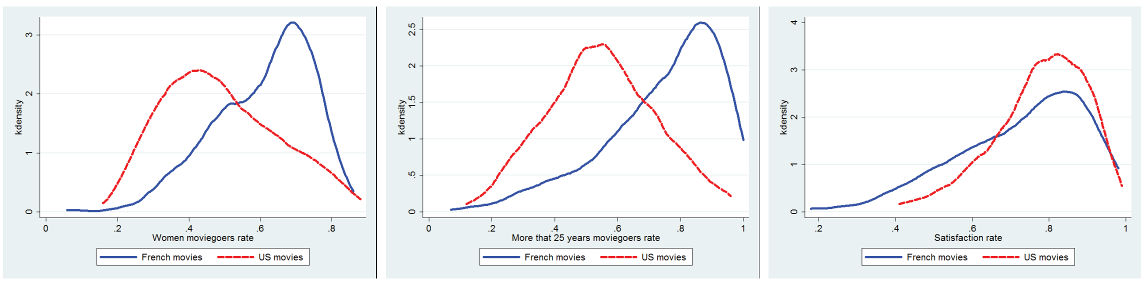
Figure 6 – Average consumers expenditures in movie theaters are stable over time
(Sources: (a) Insee, French National Account. (b) CNC)



(a) The share of consumption of movies in theaters over total consumption of households is stable.

(b) The average number of admissions per moviegoer is stable

Figure 7 – The audiences of U.S. and French movies overlap(Source: Observatoire de la satisfaction.)



(a) Women prefer French movies

(b) Elders prefer French movies

(c) French movies are more disappointing connection depends on three factors. Firstly, the length of an Internet line reduces its download speed, and homes located far away from a local exchange have lower download speed. Secondly, the diameter of the Internet cable also matters, where larger cables allow for faster connections. Last, and to a lesser extent, the technology embedded into a local exchange can affect the download speed.

A given town can be served by one local exchange point or by several local exchanges if the town is not small. Conversely, a local exchange can equip different small towns. A local exchange provides Internet access to users through Internet connections with different speed levels. The coverage rate of high speed Internet infrastructure is defined as the fraction of connections with download speeds higher than 512 kbit/s over the total number of connections delivered by a local exchange. For instance, a local exchange can reach 30,000 households, with 27,000 connections with download speeds exceeding 512 kbit/s, and the remaining connections providing download speed inferior to 512 kbits/s. The coverage rate of this local exchange is 90%. For a given town, the average coverage rate is computed using the rates of all local exchanges the connections to its inhabitants, weighted by the number of connections supplied by each local exchange. As an example, take a town provided by two local exchange. If the first local exchange can connect 30 000 households and has a high speed Internet coverage rate of 90% while the second one can connect 10 000 households and has a coverage rate of 80%, then the coverage rate of the town is 87.5%.

The number of broadband subscribers is observed in the data for all local exchanges only when they become unbundled by at least one alternative Internet service provider (ISP). The process called local loop unbundling allows an alternative ISP to propose Internet subscriptions at lower costs, and with a better service, without having to rely on the historical incumbent. However, many local exchanges were still not unbundled during the time period of the study, so that the number of subscribers is missing for many local exchanges in the data. Therefore, the number of broadband subscribers cannot be aggretated for each town the same way as it is done for the Internet coverage rate. However, it is possible to study the correlation between the coverage rate and the number of broadband subscribers at the local exchange level, using the local exchange for which we know the number of broadband subscribers.

It is noteworthy that there has been no significant change in broadband Internet infrastructure during 2008-2001. Indeed, the period of 2008-2011 corresponds to a transitory period in the development of Internet in France. It matches the end of the roll-out of high-speed Internet (DSL) and it precedes the introduction of very high Internet (optical fiber) in France. The coverage rate of broadband Internet was already very high in 2008. For instance, the percentage of lines connected to DLS technology in France increased from 99% to 99.5% over the period of 2008-2011. The main technological change that was still in progress over that period is the process called *unbundling*. The European regulation allows alternative

Internet operators to install their own equipment in the end of network facilities of the historical incumbent (the local exchange) to directly sell broadband Internet access to the final consumer. This process was initiated in 2002 in France. About 65% of lines were unbundled in 2008, to reach the number of 80% in 2011. However, this increase mainly occurred in the country-side of France as the unbundling process started first in the biggest towns of France. In our sample, i.e., the towns for which we observe movie admissions in theaters, the mean number of unbundled lines increased from 95% to 99% over the period of 2008-2011; the local exchanges located in the towns in our sample were already unbundled.

C Robustness checks for analysis 1: The correlation between the coverage rate and the use of broadband Internet

To validate the use of the coverage rate as a proxy for online piracy, we need to show that it is significantly correlated with the rate of broadband Internet subscribers. We know the number of subscribers at the local exchange level, but not for all local exchanges. A local exchange is an important piece of the ADSL infrastructure, that connects the phone line of individuals to the Internet. On average, it takes several local exchanges to serve a middle-sized town. Therefore, we do not have complete information to compute the number of broadband Internet users at the town-level. However, we can study the correlation between the broadband Internet coverage rate and the broadband Internet use rate at the local exchange level, for the local exchanges for which we observe the number of subscribers.

In practice, we estimate the following specification:

$$Subscribers_j = \beta \times CoverageRate_j + X_j'\theta + e_j \tag{6}$$

where $Subscribers_j$ is the number of subscribers of local exchange j during the first quarter of 2008 (i.e, before the Hadopi law was ever mentioned), and $CoverageRage_j$ is the percentage of lines of local exchange j that are eligible to broadband Internet. X_j accounts for additional controls.

Results are presented in Table 16. In column 1, we only include the coverage rate as an explanatory variable. The variable is positively and significantly correlated with the number of broadband subscribers. Moreover, it explains an important share of the number of broadband subscribers, as the R2 is close to 0.40. Adding the number of lines that are served by the local exchange as a control variable (column 2) leaves the results unchanged.

Table 16 – Effect of the coverage rate on the use of broadband Internet

	Number of broadband subscribers	
	(1)	(2)
Coverage rate	0.888***	0.890***
	(0.0275)	(0.0272)
Number of lines		0.00000225***
		(0.000000114)
Constant	-0.288***	-0.305***
	(0.0250)	(0.0247)
Observations	3839	3839
R-Squared	0.383	0.417

Robust standard errors. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

D Robustness checks for analysis 1: the absence of difference in pre-treatment trends

To validate the identification strategy of analysis 1, we test whether broadband use is correlated with changes in box office revenues and in American market share during the pre-HADOPI period. We focus on the period before April 2009, that is the period before the law was discussed in the public debate. To test for the absence of difference in pre-treatment trends, we estimate the following equation:

$$Outcome_{ct} = \theta_c + \delta_t + X_{ct}\beta' + \alpha \times Three\_Months\_Before_t \times Internet_c + \epsilon_{ct} \quad (7)$$

where $Three\_Months\_Before_t$ is an indicator equal to one during the three months before the HADOPI law was started o be discussed. We do not have many observation during that period preceding the debate of the HADOPI law (we only have six months), so we decide to cut the sample into half to run this test. $Outcome_{ct}$ can be the market share of U.S. movies, the number of American admissions, the number of French admissions, or the total number of admissions. Results are presented in Tables 17. They confirm the absence of differential pre-treatment trends.

Table 17 – Checking the absence of pre-treatment trends

	U.S. market share	log(U.S. adm)	log(Other adm)	log(Total adm)
	(1)	(2)	(3)	(4)
Before × Internet	-0.0653	-0.0256	0.164	0.0837
	(0.0912)	(0.348)	(0.226)	(0.220)
Town fixed effect	yes	yes	yes	yes
Month fixed effect	yes	yes	yes	yes
Quality of French films	yes	yes	yes	yes
Quality of U.S. films	yes	yes	yes	yes
Constant	yes	yes	yes	yes
Observations	760	760	703	760
R-squared	0.663	0.597	0.605	0.569

Standard errors clusters by town. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

E Additional test for analysis 1: Estimating the market expansion effect with a logit model

To try to determine the size of the market expansion effect, we add some structure by implementing a discrete choice model. Specifically, we estimate the monthly demand for movies with a logit model. Let M_{ct} be the potential consumers of each market ct (a town during a given month) that we proxy with the monthly population of that town, as obtained from the French census. We abstract from the choice of a specific movie and we model instead the choice between American and other movies, as it is the focus of this article. The utility of consumer i from buying a movie of type j (that is either American or not American) during month t in town c is given by:

$$u_{ijct} = \delta_{jct} + \epsilon_{ijct}$$

The utility is decomposed into two parts: (1) δ_{jct}, a deterministic part that is equal for all consumers, and (2) ϵ_{ijct}, a random deviation from that mean, specific to each consumer. We assume that ϵ_{ijct} is distributed extreme values.

The outside option consists of any other activities a consumer can choose instead of going to the movies. The utility of consumer i from the outside option in town c during month t is given by:

$$u_{i0ct} = \delta_{0ct} + \epsilon_{i0ct}$$

where δ_{0ct} is normalized to zero and ϵ_{i0ct} has the same properties as ϵ_{ijct}.

We specify the mean utility for choosing movie of type j in town c during month t as:

$$\begin{aligned}\delta_{jct} &= C + \alpha US_j + \rho_{cj} + \tau_{tj} + \gamma Q_{jct} \\ &\quad + \beta_1 HADOPI_t \times Internet_c + \beta_2 HADOPI_t \times Internet_c \times US_j + \xi_{jct}\end{aligned}$$

Where C is a constant, ρ_{cj} is a town fixed-effect specific to movies of nationality j, τ_{tj} is a month fixed-effect specific to movies of nationality j, US_j is a dummy equal to one for American movies, and Q_{jct} capture the quality of American or that of other (French) movies available in the market ct, as before. $HADOPI_t$ and $Internet_c$ are also defined as before. The HADOPI effect is captured with the same identification strategy as in analysis 1.

By aggregating individual choices over all consumers, the assumed distribution of ϵ_{ijct} generates the logit formula of the conditional choice probability that approximates s_{jct}, the market share of movies of type j in town c during month t:

$$s_{jct} = \frac{e^{\delta_{jct}}}{\sum_{k=0}^{J_{ct}} e^{\delta_{kct}}} \tag{8}$$

Equation 8 can be inverted to obtain the following relation that can be directly estimated with OLS:

$$\begin{aligned}\log(s_{jct}) - \log(s_{0ct}) = {} & C + \alpha US_j + \rho_{cj} + \tau_{tj} + \gamma Q_{jct} \\ & + \beta_1 HADOPI_t \times Internet_c + \beta_2 HADOPI_t \times Internet_c \times US_j + \xi_{jct}\end{aligned}$$

Results are presented in Table 18. The HADOPI effect is significantly positive for American movies while it is significantly negative for other movies. The results also reveals a general preference for American movies, and they confirm that the quality of the movies available within one alternative matters.

Table 18 – Estimates of the logit model

	$\log(s_{jct}) - \log(s_{0ct})$
U.S.	0.192***
	(0.0291)
HADOPI × Internet	-0.519***
	(0.186)
HADOPI × Internet × U.S.	1.047***
	(0.259)
Quality	0.00761***
	(0.00174)
Town × U.S. fixed effects	Yes
Town × Others fixed effects	Yes
Month × U.S. fixed effects	Yes
Month × Others fixed effects	Yes
Constant	-3.474***
	(0.0221994)
Observations	5167
R-Squared	0.984

Standard errors clustered by town. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Using the parameter estimates, we run a counterfactual simulation of what would have been the total number of admissions of American movies, of other movies, and of all movies without the HADOPI law. We compare these outcomes with the predictions of the model with the HADOPI law and we compute the difference that is induced by the anti-piracy law. Because a primary objective is to estimate whether the market expansion induced by the HADOPI law is significant or not, it is important to compute the precision of the simulated outcomes. Therefore, we bootstrap the simulations using 10000 replications, re-estimating the model each time, to obtain a distribution of the simulated outcomes. We implement a block bootstrap procedure that is clustered at the town level.

Simulated counterfactuals are presented in Table 19. They show that the HADOPI law has significantly increased by 21 million the admissions for American movies at the expense of a drop of 17 million admissions for other movies. The overall effect is positive on the total size of the market, but this effect is not statistically different from zero as it can be seen from the confidence interval. The estimated market expansion effect is about four million admissions, which is not zero, but it is small compared to the redistributive effect highlighted between U.S. and other movies. These simulations are contingent upon the sample used in this analysis. Because the sample was selected to maximize the variation in the Internet infrastructure, it is possible that the overall effect in France is smaller.

Table 19 – Counterfactual simulation of the HADOPI effect (in number of admissions)

	American movies	Other movies	All movies
HADOPI effect	20 981 866	- 17 055 861	3 926 005
95%-CI Lower	7 470 851	- 44 933 042	- 27 559 201
95%-CI Upper	37 572 159	- 3 170 752	29 178 515

F Robustness checks for analysis 1: Ruling out the advent of 3D movies

3D movies were introduced at essentially the same time as Hadopi with the release of Avatar near the end of 2009. This might have influenced the effect of the anti-piracy law because this technological innovation could have increased the demand for movies in theaters and 3D films were mainly American.[31] The effect of 3D films might also have been different across towns because the diffusion of digital projectors in France was progressive and due to limited funding.

We observe the nature of the session (i.e., whether a movie is exhibited in 3D or not) for the data provided by Médiamétrie. As a consequence, in this robustness check, we additionally control for the number of movies played in 3D in town c during month t, using only the data from Médiamétrie. In this way, we also control for the rapid conversion to digital projectors in France, as 3D movies require digital projectors to be exhibited in theaters. Results are presented in Table 20 and 21 for the U.S. market share and the log of total admissions. Columns 1-2 control for town fixed effects and month fixed effects, columns 3-4 additionally control for the time-varying quality of American movies and French movies, columns 5-6

31. Avatar was followed by other 3D releases such as How to Train Your Dragon (2010), Alice in Wonderland (2010), and so forth.

add the control for 3D screenings, and columns 7-8 contain all of the control variables and drop the 50% of towns with high-speed Internet infrastructure closest to the median.

They show that the advent of 3D movies did not interfere with the effects of the Hadopi law.

Table 20 – Estimates of parameters from equation (1) when the outcome is the U.S. market share

	U.S. market share							
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Hadopi × Internet	0.539		0.529*		0.569*		0.816**	
	(0.330)		(0.282)		(0.309)		(0.318)	
Hadopi1 × Internet		0.621		0.547		0.533		0.600
		(0.520)		(0.491)		(0.493)		(0.561)
Hadopi2 × Internet		0.840		0.766		0.780		0.979*
		(0.574)		(0.507)		(0.513)		(0.552)
Hadopi3 × Internet		0.915*		0.902**		0.959**		1.363***
		(0.505)		(0.432)		(0.463)		(0.456)
Town fixed effect	yes	yes	yes	yes	yes	yes	yes	yes
Month fixed effect	yes	yes	yes	yes	yes	yes	yes	yes
Quality of French films	no	no	yes	yes	yes	yes	yes	yes
Quality of U.S. films	no	no	yes	yes	yes	yes	yes	yes
3D shows	no	no	no	no	yes	yes	yes	yes
Constant	yes	yes	yes	yes	yes	yes	yes	yes
Observations	2087	2087	2087	2087	2087	2087	990	990
R-squared	0.880	0.880	0.886	0.886	0.886	0.887	0.892	0.893

Source: Arcep, Médiamétrie. Standard errors clustered by town. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

Table 21 – Estimates of parameters from equation (1) when the outcome is the total admissions

	log(Total Admissions)							
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Hadopi × Internet	3.585		2.872		2.959		2.351	
	(2.599)		(2.112)		(2.158)		(2.145)	
Hadopi1 × Internet		1.680		1.081		1.048		-0.170
		(1.531)		(1.545)		(1.554)		(1.821)
Hadopi2 × Internet		4.315		3.154		3.185		1.969
		(3.084)		(2.496)		(2.521)		(2.526)
Hadopi3 × Internet		4.710		3.840		3.970		2.628
		(2.999)		(2.522)		(2.557)		(2.549)
Town fixed effect	yes	yes	yes	yes	yes	yes	yes	yes
Month fixed effect	yes	yes	yes	yes	yes	yes	yes	yes
Quality of French films	no	no	yes	yes	yes	yes	yes	yes
Quality of U.S. films	no	no	yes	yes	yes	yes	yes	yes
3D shows	no	no	no	no	yes	yes	yes	yes
Constant	yes	yes	yes	yes	yes	yes	yes	yes
Obervations	2087	2087	2087	2087	2087	2087	990	990
R-squared	0.941	0.941	0.942	0.942	0.942	0.942	0.934	0.934

Source: Arcep, Médiamétrie. Standard errors clustered by town. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

G Robustness checks for analysis 2: The role of movie genres

We examine the heterogeneity of the HADOPI effect on movie admissions according to the variable movie genre, available in the dataset of this analysis. The most pirated movies are usually those aimed at a teenager audience such as Fantasy, Science Fiction, and Horror movies (see Danaher et al. (2010), Danaher and Waldfogel (2012), Variety 2019 [32], and all the yearly rankings of the most pirated movies). Therefore, we expect the HADOPI law to have a positive effect on the admissions to the most pirated films. We estimate a specification that is similar, in the spirit, to that of equation (2):

$$Outcomes_{it} = \rho_t + \beta X_i + \gamma US_i + \sum_{\substack{k \\ k \neq com}} \alpha_k \times HADOPI_t \times \mathbb{1}_{[i \in Genre_k]} + \epsilon_{it} \tag{9}$$

We use the logarithm of admissions during the release week and the logarithm of the ratio between the number of admissions during the release week and the corresponding number of screens as dependent variables. Movies are grouped in six separated genres: adventure, animated, comedy, drama, sci-fi/fantasy/horror, and thriller/crime. The sci-fi/fantasy/horror genre contains most of the U.S. blockbusters such as superhero movies that are the most pirated ones. As shown in Table 22, the comedy genre is the most frequent genre, representing 37% of movies in our sample, and the sci-fi/fantasy/horror genre is almost entirely composed of American movies. We use the comedy genre as reference group in our specification. In an alternative specification, we also decompose the HADOPI effect on movie genres between American and French movies to obtain more detailed effects.

Table 22 – Distribution of movies by genre and nationality

Genre	All movies	French movies	U.S. movies
Animated	8,5%	27,9%	72,1%
Adventure	17,5%	16,4%	83,6%
Comedy	37,3%	61,5%	38,5%
Drama	16,6%	62,4%	37,6%
Thriller / Crime	11,0%	50,0%	50,0%
SF / Fantasy / Horror	9,2%	4,1%	95,9%
Total	767	44,4%	55,6%

Columns (1) and (3) of Table 23 present the estimated results of equation 9 without differentiating between American and French movies. The HADOPI law significantly increases the admissions to sci-fi/fantasy/horror movies while it decreases those to drama, thriller/crime, and adventure movies. The anti-piracy law has no effect on animated movies. Columns (2) and (4) decompose the HADOPI effect according to movie genres between American and French movies. The HADOPI law significantly increases the admissions to American sci-fi/fantasy/horror movies (there are no French sci-fi/fantasy/horror movies

32. https://variety.com/2019/digital/news/avengers-endgame-piracy-box-office-1203198888/

in our sample), at the expense of French adventure, drama, and thriller/crime movies. This finding helps to understand why the effect of HADOPI is different between American and other (French) movies and to identify the type of cultural products whose production is potentially affected by the anti-piracy law.

Table 23 – Heterogeneity of the HADOPI effect on movie admissions according to the movie genre

	log(Admissions)		log(Admissions/Screens)	
	(1)	(2)	(3)	(4)
HADOPI × Anim.	0.0142		-0.0142	
	(0.163)		(0.157)	
HADOPI × Adven.	-0.123		-0.156*	
	(0.0904)		(0.0904)	
HADOPI × Drama	-0.211**		-0.188**	
	(0.0891)		(0.0924)	
HADOPI × SF_Fan_Hor	0.326***		0.380***	
	(0.122)		(0.130)	
HADOPI × Thril_Crime	-0.209**		-0.258**	
	(0.105)		(0.104)	
HADOPI × Anim. × FR		-0.00900		-0.0699
		(0.170)		(0.166)
HADOPI × Anim. × US		0.0186		0.00280
		(0.190)		(0.185)
HADOPI × Adven. × FR		-0.336***		-0.385***
		(0.126)		(0.126)
HADOPI × Adven. × US		-0.0865		-0.116
		(0.0940)		(0.0942)
HADOPI × Drama × FR		-0.231**		-0.216**
		(0.0976)		(0.101)
HADOPI × Drama × US		-0.184		-0.148
		(0.113)		(0.119)
HADOPI × SF_Fan_Hor × FR		0		0
		(.)		(.)
HADOPI × SF_Fan_Hor × US		0.328***		0.382***
		(0.122)		(0.131)
HADOPI × Thril_Crime × FR		-0.241**		-0.296**
		(0.113)		(0.116)
HADOPI × Thril_Crime × US		-0.170		-0.210
		(0.159)		(0.149)
log(Screens)	1.298***	1.295***		
	(0.0765)	(0.0763)		
log(Ad)	0.197***	0.196***	0.309***	0.305***
	(0.0436)	(0.0438)	(0.0379)	(0.0383)
log(Budget)	-0.0302	-0.0289	0.0395	0.0405
	(0.0383)	(0.0382)	(0.0363)	(0.0363)
Consumer rating	0.181***	0.186***	0.175***	0.181***
	(0.0404)	(0.0406)	(0.0416)	(0.0419)
Press rating	0.121***	0.116***	0.129***	0.124***
	(0.0302)	(0.0303)	(0.0302)	(0.0304)
Genre fixed effect	yes	yes	yes	yes
Nationality fixed effect	yes	yes	yes	yes
Art and house fixed effect	yes	yes	yes	yes
Age restriction fixed effect	yes	yes	yes	yes
Distributor fixed effect	yes	yes	yes	yes
Month fixed effect	yes	yes	yes	yes
Constant	yes	yes	yes	yes
N	802	802	802	802
R^2	0.804	0.804	0.460	0.463

Source: Allocine, CNC, Kantar Media. Robust standard errors. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

H Robustness checks for analysis 2: Ruling out the informative effect explanation

In this robustness check, we rule out the long-tail explanation proposed by Peukert et al. (2017), that is, informative effect of online piracy benefits small movies. If the informative effect was explaining our results, then blockbuster films would have benefited from higher revenues after the HADOPI law. Therefore, we estimate the following equation in a difference-in-differences setting:

$$Admissions_{it} = \rho_t + \gamma \times Size_i + \alpha \times HADOPI_t \times Size_i + \beta X_i + \epsilon_{it} \tag{10}$$

for movie i during release week t, where ρ_t is a week fixed effect, where $Size_i$ is a dummy variable equal to one when a movie's size is above its median, where $HADOPI_t$ is a post-HADOPI dummy variable equal to one after November 2009, and where X_i is a set of movie variables including the production budget, consumers' rating, press rating, fixed effects for genre, nationality, art-house movies, age restrictions, and distributors. We test two variables for the size of a movie: the total advertising expenditures and the number of screens during the release week. The production budget is not a good indicator of the potential audience of a movie in the French theatrical market, as American movies usually have higher production budgets than French ones because they are designed to be sold on much more markets (countries). The advertising expenditures and the number of opening screens reflect the expectations of distributors about movies' revenues. Results are presented in Table 24 and demonstrate the absence of a positive effect on revenues of blockbuster films after the introduction of the HADOPI law when a blockbuster is defined in terms of high advertising expenditures (Column 1) or high number of opening screens (Column 2).

This test would not be valid if the absence of an increase in the revenues of blockbuster films after the HADOPI law was hiding an increase in revenues to American blockbusters compensating a decrease in revenues of French ones. We confirm the validity of the previous test by estimating the following equation in a triple-difference setting:

$$\begin{aligned} Admissions_{it} =& \rho_t + \gamma \times Size_i + \delta \times US_i + +\lambda US_i \times Size_i + \mu \times HADOPI_t \times US_i \\ &+ \alpha \times HADOPI_t \times Size_i + \phi \times HADOPI_t \times US_i \times Size_i + \beta X_i' + \epsilon_{it} \end{aligned} \tag{11}$$

where $Size_i$ and $HADOPI_t$ are defined are before, where US_i is an indicator equal to one for U.S. movies, and where X_i is a set of movie variables including the production budget, consumers' rating, press rating, fixed effects for genre, art-house movies, age restrictions, and distributors. With this specification, we identify separately the anti-piracy law effect on American blockbuster films and on French ones. Results are presented in Column 3 and 4 and they confirm the absence of a positive effect on admissions to American blockbuster film after the anti-piracy law was adopted. This effect is actually negative although non significant.

Overall, these results are contradictory with the mechanism proposed in Peukert et al. (2017). We do not find that American blockbuster films have benefited more from the anti-piracy law. Therefore, an informative effect from online piracy profitable to small independent films does not explain our results.

Table 24 – DiD small vs. blockbuster film in France (first week): ruling out the information effect explanation

	log(Admissions)			
	(1)	(2)	(3)	(4)
High_Ad	0.482***	0.498***	0.329***	0.488***
	(0.0745)	(0.0641)	(0.112)	(0.0646)
High_Op_Screens	0.610***	0.600***	0.604***	0.424***
	(0.0572)	(0.0690)	(0.0570)	(0.0922)
HADOPI × High_Ad	0.0314		0.0556	
	(0.0859)		(0.137)	
HADOPI × High_Op_Screens		0.0180		0.123
		(0.0836)		(0.123)
HADOPI × U.S.			0.220*	0.281**
			(0.121)	(0.115)
U.S. × High_Ad			0.305**	
			(0.133)	
U.S. × High_Op_Screens				0.339***
				(0.118)
HADOPI × U.S. × High_Ad			-0.132	
			(0.187)	
HADOPI × U.S. × High_Op_Screens				-0.217
				(0.170)
Observations	814	814	814	814
R-squared	0.669	0.669	0.674	0.675

Source: Allocine, CNC, Kantar Media.
Robust standard errors. + $p < 0.10$, * $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$
The regressions control for: log(Screens), log(Ad), log(Budget), Consumer rating, Press rating, and a constant. They also control for Genre, Nationality, Art and House, Age restriction, Month, and Distributor fixed effects.

I Robustness checks for analysis 2: Extreme values

Table 25 – DiD French vs. U.S. in France (first week), a robustness test on demand reaction

	log(Admissions)		log(Admissions/Screens)	
	(1)	(2)	(3)	(4)
HADOPI $\times U.S.$	0.146***		0.130***	
	(0.0469)		(0.0481)	
HADOPI1 $\times U.S.$		0.192**		0.228***
		(0.0796)		(0.0827)
HADOPI2 $\times U.S.$		0.294***		0.305***
		(0.0616)		(0.0622)
HADOPI3 $\times U.S.$		0.101*		0.0889
		(0.0566)		(0.0578)
N	656	656	656	656
R^2	0.915	0.918	0.708	0.707

Source: Allocine, CNC, Kantar Media.
Robust standard errors. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$
The regressions control for: log(Screens), log(Ad), log(Budget), Consumer rating, Press rating, and a constant. They also control for Genre, Nationality, Art and House, Age restriction, Month, and Distributor fixed effects.
Estimates obtained after having dropped the 20% of movies with the highest absolute residual values from the first-step estimate.

J Control group selection for analysis 3

During the period 2008-2011, no measure similar to the French HADOPI law has been implemented in Europe, besides Sweden in 2009. However, three waves of legislation in countries close to France may have stirred up the Internet users community, but we believe they did not have any significant impact on individuals because they have not been implemented. In Spain, in 2010, discussions were surrounding the Sinde Law, a provision designed to shut down websites in violation with copyright law. It was made law at the end of 2011. In Italy, in 2011, the regulation and competition authority for the communication industries, the AGCOM, expressed its intention to fight websites in violation with copyright law. The Spanish and the Italian measures are of quite a different nature compared to the HADOPI law. Finally in the United Kingdom, in 2010, the Digital Economy Act addressed online copyright infringement in a similar way to the graduated response of the HADOPI law. With this act, Internet subscribers who had downloaded illegal content using peer-to-peer file-sharing systems were supposed to receive notifications. This Act is in force although the procedure against infringers has not been implemented.

We then run the following estimation using observations in the pre-treatment period (i.e form January 2007 to March 2009) to select the relevant candidate to be included in the control group:

$$Outcome_{Fr,t} = \alpha + \beta_s Outcome_{ct} + \epsilon_{ct} \tag{12}$$

c is a country and t is a month, with $Outcome_{ct}$ being repetitively $\log(Admissions_{ct}/Screens_{ct})$ for US movies, $\log(Screens_{ct})$ for US movies, Lag_{ct} for US movies, $\log(Admissions_{ct})$ for all movies, and $\log(USmarketshare_{ct})$.

Table 26 – $\log(Admissions_{ct}/Screens_{ct})$ (January 2007 - March 2009)

	Belgium (1)	Finland (2)	Germany (3)	Italy (4)	Netherlands (5)	Spain (6)	Switzerland (7)	UK (8)
log(Admissions/Screens)	0.459***	0.381***	0.368***	0.223	0.395***	0.432*	0.409***	0.301***
	(0.128)	(0.116)	(0.0962)	(0.144)	(0.0795)	(0.245)	(0.141)	(0.0714)
Constant	3.672***	4.384***	4.397***	5.304***	4.246***	3.908**	4.170***	4.735***
	(0.855)	(0.724)	(0.619)	(0.939)	(0.522)	(1.605)	(0.897)	(0.497)
Observations	27	27	27	27	27	27	27	27
R-squared	0.329	0.464	0.396	0.109	0.372	0.301	0.365	0.437

Source: ScreenDaily.com. Standard errors with Newey-West corrections allowing for observations within a country to be correlated up to 6 months. *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$.

Our preferred control group when the outcome of interest is the number of admissions over the number of screens of US movies (Table 26) is constituted by Belgium, Finland, Germany, the Netherlands, Spain, Switzerland, and United Kingdom. Our preferred control group when the outcome of interest is the

Table 27 – log($Screens_{ct}$) (January 2007 - March 2009)

	Belgium (1)	Finland (2)	Germany (3)	Italy (4)	Netherlands (5)	Spain (6)	Switzerland (7)	UK (8)
log(Screens)	0.304**	0.123	0.139	-0.168*	0.379*	-0.0672	0.0485	0.0674
	(0.109)	(0.120)	(0.144)	(0.0943)	(0.191)	(0.130)	(0.134)	(0.193)
Constant	6.262***	7.464***	6.946***	9.396***	5.696***	8.611***	7.802***	7.512***
	(0.661)	(0.610)	(1.168)	(0.756)	(1.202)	(1.043)	(0.742)	(1.608)
Observations	27	27	27	27	27	27	27	27
R-squared	0.132	0.020	0.024	0.041	0.090	0.003	0.004	0.003

Source: ScreenDaily.com. Standard errors with Newey-West corrections allowing for observations within a country to be correlated up to 6 months.
*** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$.

Table 28 – Lag_{ct} (January 2007 - March 2009)

	Belgium (1)	Finland (2)	Germany (3)	Italy (4)	Netherlands (5)	Spain (6)	Switzerland (7)	UK (8)
Lag	0.473***	0.456	-0.119	0.322***	-0.0420	-0.404***	-0.0671	0.405**
	(0.118)	(0.271)	(0.166)	(0.104)	(0.0395)	(0.0609)	(0.109)	(0.147)
Constant	2.565**	3.722**	8.031***	3.282**	7.322***	11.42***	7.443***	4.886***
	(1.241)	(1.694)	(1.960)	(1.468)	(0.804)	(0.820)	(0.761)	(1.058)
Observations	27	27	27	27	27	27	27	27
R-squared	0.172	0.080	0.011	0.141	0.004	0.207	0.004	0.113

Source: ScreenDaily.com. Standard errors with Newey-West corrections allowing for observations within a country to be correlated up to 6 months.
*** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$.

Table 29 – log($Admissions_{ct}$) (January 2007 - March 2009)

	Belgium (1)	Finland (2)	Germany (3)	Italy (4)	Netherlands (5)	Spain (6)	Switzerland (7)	UK (8)
log(Admissions)	0.751***	0.0478	0.519***	0.0541	0.405***	0.351*	0.398***	0.321*
	(0.105)	(0.0759)	(0.0809)	(0.0449)	(0.132)	(0.174)	(0.116)	(0.176)
Constant	6.056***	15.87***	8.284***	15.64***	10.81***	10.99***	11.10***	11.34***
	(1.453)	(0.960)	(1.306)	(0.666)	(1.885)	(2.738)	(1.577)	(2.835)
Observations	27	27	27	27	27	27	27	27
R-squared	0.660	0.003	0.346	0.016	0.158	0.073	0.250	0.095

Source: ScreenDaily.com. Standard errors with Newey-West corrections allowing for observations within a country to be correlated up to 6 months.
*** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$.

Table 30 – log($Admissions_{ct}/Screens_{ct}$) (January 2007 - March 2009)

	Belgium (1)	Finland (2)	Germany (3)	Italy (4)	Netherlands (5)	Spain (6)	Switzerland (7)	UK (8)
log(Admissions/Screens)	1.918***	0.347	1.581***	0.955***	0.389	0.819*	3.370***	2.134**
	(0.410)	(0.320)	(0.290)	(0.330)	(0.288)	(0.468)	(0.401)	(1.002)
Constant	-0.124*	-0.471***	-0.150***	-0.234**	-0.485***	-0.449***	0.0485	-0.406***
	(0.0680)	(0.153)	(0.0535)	(0.101)	(0.134)	(0.122)	(0.0583)	(0.136)
Observations	27	27	27	27	27	27	27	27
R-squared	0.684	0.072	0.535	0.298	0.041	0.062	0.614	0.109

Source: ScreenDaily.com. Standard errors with Newey-West corrections allowing for observations within a country to be correlated up to 6 months.
*** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$.

number of screens of US movies (Table 27) is constituted by Belgium, and the Netherlands. Our preferred control group when the outcome of interest is the time lag of US movies (Table 28) is constituted by Belgium, Italy, and United Kingdom. Our preferred control group when the outcome of interest is the number of admissions of all movies (Table 29) is constituted by Belgium, Germany, the Netherlands, Spain, Switzerland, and United Kingdom. Finally, our preferred control group when the outcome of interest is the number of admissions over the number of screens of all movies (Table 30) is constituted by Belgium, Germany, Italy, Spain, Switzerland, and United Kingdom.

Figure 8 – Countries included in the control group for the Log(Admissions/Screens) of US movies.

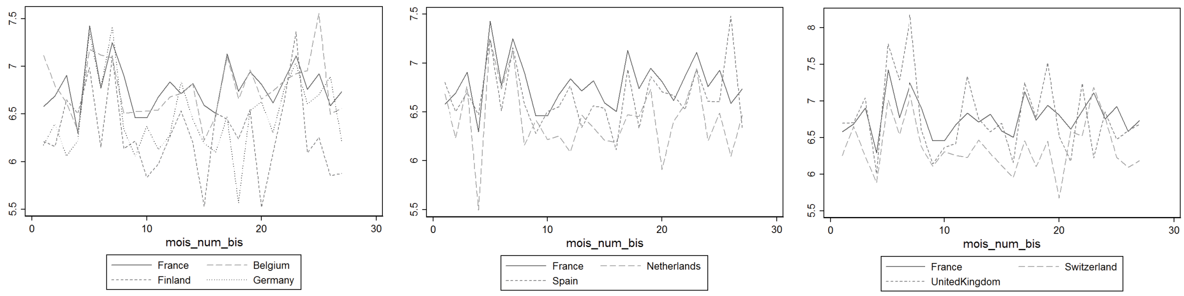


Figure 9 – Countries not included in the control group for the Log(Admissions/Screens) of US movies.

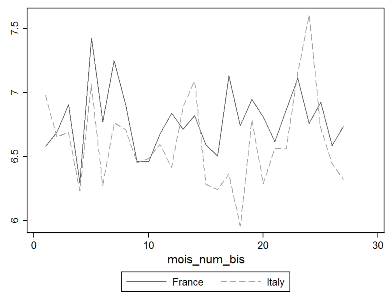


Figure 10 – Countries included in the control group for the Log(Screens) of US movies.

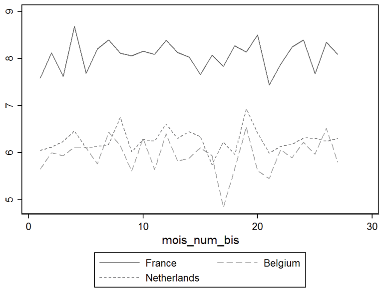
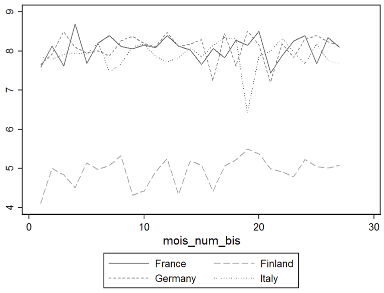


Figure 11 – Countries not included in the control group for the Log(Screens) of US movies.



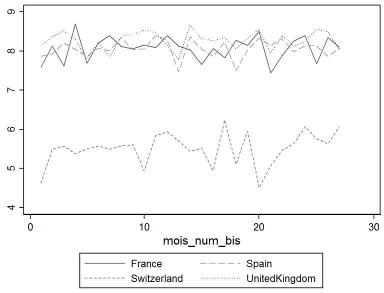


Figure 12 – Countries included in the control group for the time Lag of US movies.

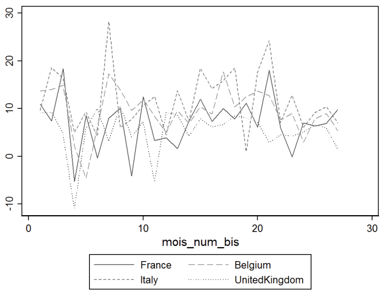
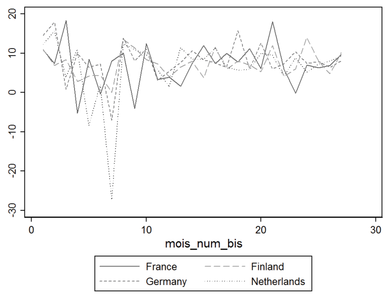


Figure 13 – Countries not included in the control group for the time Lag of US movies.



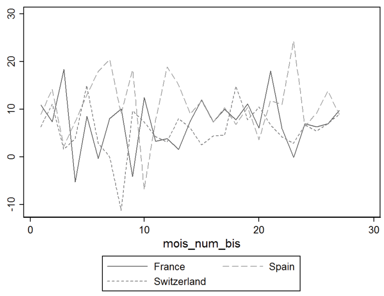


Figure 14 – Countries included in the control group for the aggregate number of admissions of all movies.

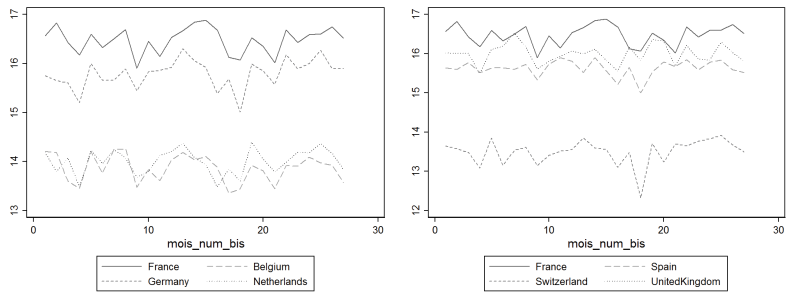


Figure 15 – Countries not included in the control group for the aggregate number of admissions of all movies.

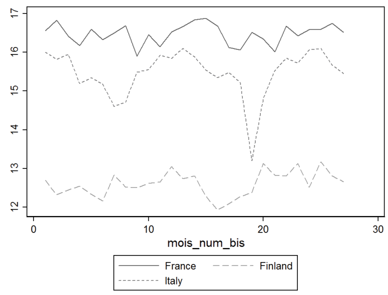


Figure 16 – Countries included in the control group for the US market share.

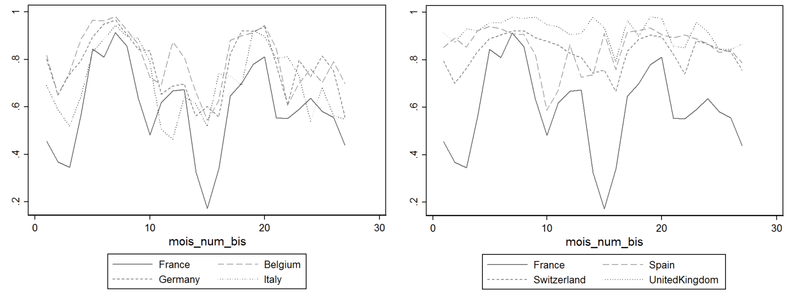
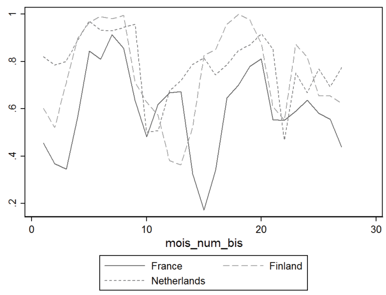


Figure 17 – Countries not included in the control group for the US market share.



K Interpretation of coefficients in the triple-differences approach of analysis 4

A simplified version of the equation (5) we estimate in section 5.4 is the following one :

$$
\begin{aligned}
Y_{ijta} =& \gamma_i + \lambda_t + \delta_a + \alpha After_t * USA_i + \rho_1 USA_i * Young1_a + \rho_2 USA_i * Young2_a \\
& + \eta_1 After_t * Young1_a + \eta_2 After_t * Young2_a + \beta_1 After_t * USA_i * Young1_a \\
& + \beta_2 After_t * USA_i * Young2_a + \epsilon_{ijta}
\end{aligned}
$$

Then, we define six differences:

$$
\begin{aligned}
(1)\ & E\left[Y_{ijta}|i = USA, a = Young1, t = After\right] - E\left[Y_{ijta}|i = USA, a = Young1, t = Before\right] \\
& = \gamma_{USA} + \lambda_{After} + \delta_{Young1} + \alpha + \rho_1 + \eta_1 + \beta_1 - \gamma_{USA} - \lambda_{Before} - \delta_{Young1} - \eta_1 \\
& = \lambda_{After} - \lambda_{Before} + \alpha + \rho_1 + \beta_1
\end{aligned}
$$

$$
\begin{aligned}
(2)\ & E\left[Y_{ijta}|i = Fr, a = Young1, t = After\right] - E\left[Y_{ijta}|i = Fr, a = Young1, t = Before\right] \\
& = \gamma_{Fr} + \lambda_{After} + \delta_{Young1} + \rho_1 - \gamma_{Fr} - \lambda_{Before} - \delta_{Young1} \\
& = \lambda_{After} - \lambda_{Before} + \rho_1
\end{aligned}
$$

$$
\begin{aligned}
(3)\ & E\left[Y_{ijta}|i = USA, a = Young2, t = After\right] - E\left[Y_{ijta}|i = USA, a = Young2, t = Before\right] \\
& = \gamma_{USA} + \lambda_{After} + \delta_{Young2} + \alpha + \rho_2 + \eta_2 + \beta_2 - \gamma_{USA} - \lambda_{Before} - \delta_{Young2} - \eta_2 \\
& = \lambda_{After} - \lambda_{Before} + \alpha + \rho_2 + \beta_2
\end{aligned}
$$

(4) $E\left[Y_{ijta}|i = Fr, a = Young2, t = After\right] - E\left[Y_{ijta}|i = Fr, a = Young2, t = Before\right]$

$= \gamma_{Fr} + \lambda_{After} + \delta_{Young2} + \rho_2 - \gamma_{Fr} - \lambda_{Before} - \delta_{Young2}$

$= \lambda_{After} - \lambda_{Before} + \rho_2$

(5) $E\left[Y_{ijta}|i = USA, a = Old, t = After\right] - E\left[Y_{ijta}|i = USA, a = Old, t = Before\right]$

$= \gamma_{USA} + \lambda_{After} + \delta_{Old} + \alpha - \gamma_{USA} - \lambda_{Before} - \delta_{Old}$

$= \lambda_{After} - \lambda_{Before} + \alpha$

(6) $E\left[Y_{ijta}|i = Fr, a = Old, t = After\right] - E\left[Y_{ijta}|i = Fr, a = Old, t = Before\right]$

$= \gamma_{Fr} + \lambda_{After} + \delta_{Old} - \gamma_{Fr} - \lambda_{Before} - \delta_{Old}$

$= \lambda_{After} - \lambda_{Before}$

With those six differences, we can give the interpretation of β_1 and β_2 using difference-in-difference-in-differences:

$$\beta_1 = [(1) - (2)] - [(5) - (6)] \tag{13}$$

$$\beta_2 = [(3) - (4)] - [(5) - (6)] \tag{14}$$

As a result, β_1 (resp. β_2)can be interpreted as the difference in Y for U.S. movies compared to French movies, between consumers aged 10-29 (resp. 30-49) and consumers aged 50-80, after and before the law is implemented. Then, it is direct to see that the coefficients η_a capture the difference in Y for French movies between young and old consumers, after and before the law. This effect is captured through the sum $\beta + \eta$ for U.S. movies. The total effect, for French and U.S. movies, is captured by $2 \times \eta + \beta$.

L Perspectives and summary of the results

The estimated values of the HADOPI effect from the four empirical analyses are different, but we show below that they have similar implications after some adjustments are made to compute the total change in the number of admissions to U.S. films in France after the law.

The total number of admissions was different before and after the law, but we are only interested in the differences that are attributable to the law. Our estimation results show statistically weak evidence of a demand creation effect caused by the law. As an approximation to compute the overall effects on the admissions to American movies or on the market share of American movie sales, we fix the total number of admissions before and after the law to a constant value. Then, we note that the U.S. films' market share was equal to 48% after the HADOPI law was passed and that the total number of admissions over the post-HADOPI period was approximately 440 million. Finally, we use the distribution of broadband Internet coverage rate presented in table 3 to compute the effect from the town-level approach, and the consumer age distribution to compute the effect from the consumer-level approach.[33] The implied effects are shown in Table 31.

Table 31 – Comparison of the results and variation in revenue and consumer loss

	Analysis 1: Town level approach	Analysis 2: U.S. *vs* French movies in France	Analysis 3: International comparisons	Analysis 4: Consumer level approach
Estimated coefficient	Increase in the U.S. market share by 0.6 percentage point when the high speed Internet use rate increase by 1 percentage point	Increase in the number of admissions to U.S. films by 10%	Increase in the U.S. market share by 8%	Increase in the number of admissions to U.S. films for consumers aged 10-29 (resp. 30-49) by 20% (resp. 10%)
Rise in the market share of U.S. films	10%	10%	8%	10%
Rise in the number of admissions to U.S. films (in million)	19.2	19.2	15.4	20.0
Rise in the revenue to U.S. films (in euros million)	121	121	97	126
Number of consumers involved in the redistribution (in million)	2.5	2.5	2.8	2.9

Lecture note: For instance, with a rise in the market share of US films equal to 10%, we obtain a rise in the number of admissions to US films equal to 19.2 million ($0.48 \times 440-(0.48 \times 440/1.10)=19.2$).

With an increase in the U.S. market share of approximately 9%, the increase in U.S. film admissions after the law is between 15.4 and 20.0 million. It involves a decrease in admissions to French films of

33. The distribution of moviegoers' age in France is given by the CNC and is as follows: 42.8% are aged between 6 and 29, 25.8% are aged between 30 and 49, and 31.4% are aged 50 and over.

approximately the same amount. Given that the average ticket price was 6.3 euros in France during the post-HADOPI period, U.S. movies benefited from an increase in sales of between 97 and 126 million euros. On average, a distributor collects 38% of ticket revenue. As a consequence, the transfer in revenue from French movie distributors to U.S. distributors is between 37 and 48 million euros. Assuming that the distribution of consumers involved in the redistributive effect of the HADOPI is the same as the distribution of moviegoers, we find that between 2.2 and 2.9 million individuals switched from French movies to American ones in theaters after the implementation of the law, that is about 7% of moviegoers. [34]

Table 32 provides a summary of the results of the four empirical analyses in the form of their pros and cons to show the complementary between them.

Table 32 – Summary of each empirical strategy

	Main effects identified	Results	Pros	Cons
(1) Local comparisons: towns with high level vs. towns with low level of online piracy	Local market expansion effect and business stealing effect in towns with high level of online piracy compared to ones with low level of online piracy	- No significant market expansion effect but business stealing effect - The market share of U.S. movies increases by 0.8% with a one percentage point increase of the broadband internet use rate	- Main effects of the HADOPI law are captured - Rules out simultaneous unrelated shocks specific to U.S. or to French movies	No conclusion at the national level: localized effect on middle-sized towns
(2) National comparisons: U.S. movies vs. French movies in France	Relative business stealing effect of U.S. movies toward French movies	- Relative increase of U.S. films admissions by 10% relatively to French films - No reaction from the supply side of U.S. movies compared to French movies, except a decrease in the production budget, a decrease in user ratings, but an increase in the marketing expenditures	- Checks for supply reactions from U.S. film distributors compared to French film distributors - Controls for simultaneous unrelated shock symmetric on all movies in France	- No conclusion on market expansion effect and pure business stealing effect - Does not check for simultaneous unrelated shocks specific to U.S. or to French movies
(3) International comparisons: France vs. other European countries	Market expansion effect in France and business stealing effect from U.S. movies in France, compared to other countries	- Business stealing effect: market share of U.S. movies increases by 8% and weak evidence of a 8% market expansion effect - No change in the speed nor in the quantities of exports of U.S. films to France	- Main effects of the HADOPI law are captured - Checks for supply side reactions of film distributors of U.S. movies in France compared to other European countries	- Does not control for simultaneous unrelated shocks in France in general, or specific to U.S. or French movies - Does not check for supply side reactions of U.S. film distributors compared to French film distributors, in France
(4) Consumer comparisons: consumers with high propensity vs. those with low propensity to download	Business stealing effect of U.S. movies toward French movies and market expansion effect relative to older consumers with low propensity to download	- Increase in U.S. films admissions of 20% for consumers aged 10-29 and of 10% for consumers aged 30-49, compared to consumers aged 50-80 - No market expansion effect: similar decrease in admissions to other films for consumers aged 10-29 and 30-49 compared to consumers aged 50-80	- Main effects of the HADOPI law are captured - Distinguishes what type of consumers are influenced by the new regulation	- Very localized data collection

34. The increase in U.S. admissions is approximately 11.8 to 15.4 million per year. The distribution of moviegoers' attendance in France is given by the CNC: each year on average, 1.5 million assiduous moviegoers generate 44 million admissions, 11.1 million regular moviegoers generate 95 million admissions, and 24.5 million casual moviegoers generate 60 million admissions. Using these figures, it is immediate to obtain the number of individuals involved in the redistributive effect of the law.