## The Pirate Bay & Box Office Buccaneers

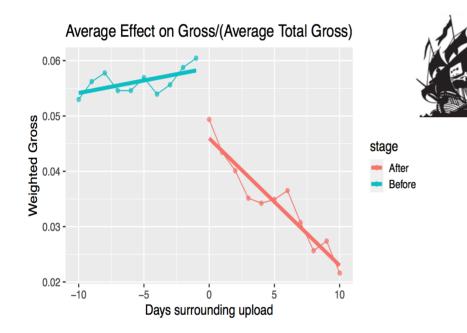


Figure 7: 10 days before and after the arrival of a good quality torrent

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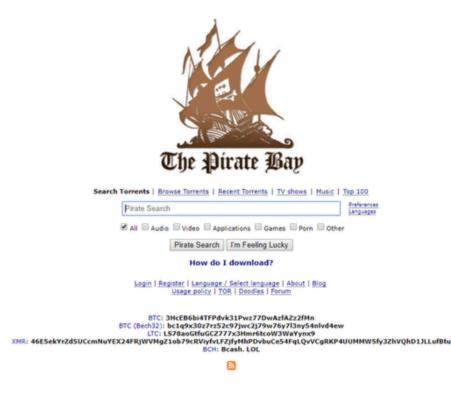




## The Challenge: Measuring digital piracy

#### **Digital Piracy**

- Digital piracy is the act of distributing or consuming content online without permission or payment
- A torrent is a link to a downloadable file through Peer-to-Peer technology; The Pirate Bay (TPB) is a catalogue of torrents
- Piracy has forced major change in media industries
- TPB is and has been the leading torrent catalogue on the Internet
- The web archive has an archive of all their files + scripts to update it to the most recent ones



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# To what extent does piracy displace legitimate sales, and do all firms suffer equally ?

#### Literature

- Revenue displacement in movies: Danaher and Waldfogel (2012), Smith and Telling 2012, Danaher and Smith (2014) e.g Megaupload
- Revenue increase in movies: Lu et al. (2019)
- Mixed results in music: Piracy is/was widespread with music, some studies find a displacement effect (e.g Hui and Png (2003) or Peitz and Waelbroeck(2004) others do not (e.g., Aguiar and Martens (2016))
- Digital goods vs physical goods: Qian (2014) investigates the effect of counterfeit products by quality tier in the fashion industry.



# Identification strategy exploits the random arrival of a good quality copy

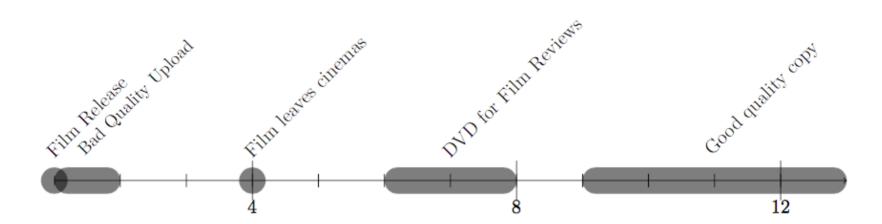


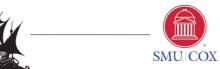
Figure 1: Theoretical timeline for the expected upload of a torrent

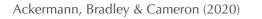
Table 1: Average	days to upload	by torrent quality
	Good Quality	Bad Quality
Average Days	29	17
Median Days	15	9

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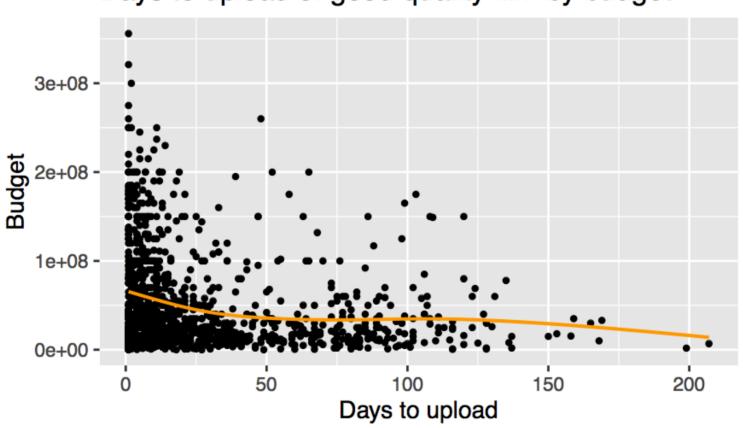
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# Identification strategy exploits the random arrival of a good quality copy



Days to upload of good quality film by budget

Figure 2: Average days to good quality uploads by budget







# Identification strategy exploits the random arrival of a good quality copy

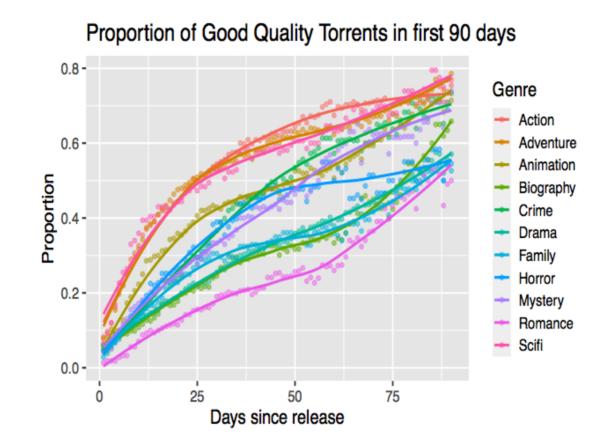


Figure 3: Average proportion of good torrents over time by genre





## Splitting the data, pre and post of the arrivals of a good quality copy

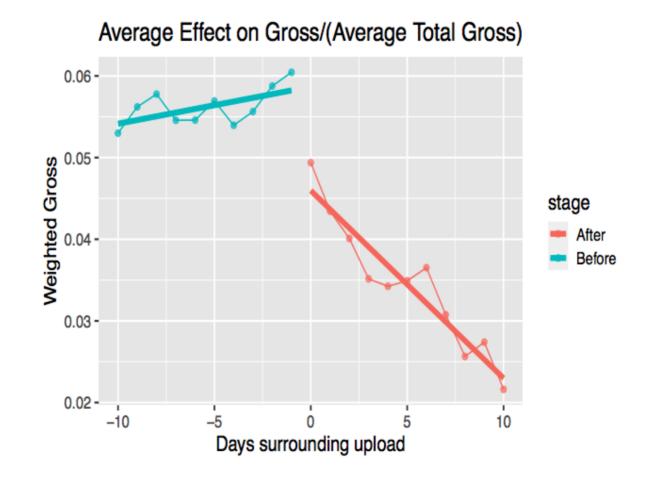


Figure 7: 10 days before and after the arrival of a good quality torrent



Ackermann, Bradley & Cameron (2020)

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	(1)
VARIABLES	All Movies
bad_quality_dummy	$0.0320^{**}$
	(0.0153)
good_quality_dummy	-0.161***
	(0.0160)
Observations	110,792
$R^2$	0.869
Movie FE	Yes
Days since release FE	Yes
Year-Week FE	Yes
Number of movies	2145
D 1 1 1	

 $InRevenue_{ijt} = \beta_1 Bad_Quality_{ijt} + \beta_2 Good_Quality_{ijt} + X_{ijt} + \mu_i + \Upsilon_j + \phi_t + \varepsilon_{jt} \quad (1)$ 

Robust standard errors in parentheses

\*\*\* p<0.01, \*\* p<0.05, \* p<0.1









	(1)	(2)	(3)
VARIABLES	Movies <p25< td=""><td>Movies IQ</td><td>Movies &gt;P75</td></p25<>	Movies IQ	Movies >P75
bad_quality_dummy	-0.344***	0.027	0.149***
	(0.040)	(0.021)	(0.027)
good_quality_dummy	0.227***	-0.124***	-0.048**
	(0.044)	(0.022)	(0.022)
Observations	28,775	54,736	27,281
$R^2$	0.845	0.870	0.926
Movie FE	Yes	Yes	Yes
Days since release FE	Yes	Yes	Yes
Year-Week FE	Yes	Yes	Yes
Number of movies	712	1026	407

Table 3: Budget subset

Robust standard errors in parentheses

\*\*\* p<0.01, \*\* p<0.05, \* p<0.1

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### Estimation: Heterogeneity by genre

Table 4: Genre subset 1					Negative	
VARIABLES	(1) Action 0.063**	(2) Adventure 0.092***	(3) Animation -0.116**	(4) Biography 0.493***	(5) Comedy -0.106***	impact on genres with focus on story
Dau_quanty_dummy	(0.003)	(0.030)	(0.050)	(0.070)	(0.022)	
good_quality_dummy	-0.050** (0.021)	-0.046* (0.026)	-0.005 (0.054)	-0.646*** (0.078)	-0.210*** (0.024)	
$\begin{array}{c} \text{Observations} \\ R^2 \end{array}$	$32,842 \\ 0.927$	$26,300 \\ 0.915$	9,309 0.921	$12,051 \\ 0.855$	$41,\!615$ 0.882	
Movie FE	Yes	Yes	Yes	Yes	Yes	
Days since release FE	Yes	Yes	Yes	Yes	Yes	
Year-Week FE	Yes	Yes	Yes	Yes	Yes	
Number of movies	589	412	143	220	770	
	Robust st	andard errors i	n parentheses			

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\*\*\* p<0.01, \*\* p<0.05, \* p<0.1





## Estimation: Heterogeneity by genre

Table 5: Genre subset 2				Postive		
VARIABLES	(1) Crime -0.020	(2) Drama 0.014	(3) Family 0.081*	(4) Fantasy 0.304***	(5) Horror -0.143***	impact on genres with focus on experience
good_quality_dummy	(0.041) 0.018 (0.039)	(0.025) - $0.158^{***}$ (0.028)	(0.046) - $0.186^{***}$ (0.061)	(0.060) -0.006 (0.056)	(0.035) $0.344^{***}$ (0.037)	
Observations $R^2$ Movie FE Days since release FE Year-Week FE Number of movies	17,333 0.904 Yes Yes Yes 377	55,535 0.830 Yes Yes Yes 1142	7,433 0.941 Yes Yes Yes 133	9,213 0.929 Yes Yes Yes 175	9,510 0.965 Yes Yes Yes 225	

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Robust standard errors in parentheses

\*\*\* p<0.01, \*\* p<0.05, \* p<0.1



Ackermann, Bradley & Cameron (2020)



# What is the effect on a movie's Box office revenue of the arrival of a good quality copy of a competing movie in the same genre released the same date ?

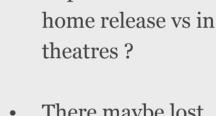
	(1)	(2)	(3)	(4)	(5)
VARIABLES	Action	Adventure	Animation	Biography	Comedy
				0.0	
bad_quality_dummy	0.063**	0.093***	-0.109**	0.497***	-0.109***
	(0.027)	(0.030)	(0.050)	(0.070)	(0.022)
good_quality_dummy	0.028	-0.146***	-0.141**	-0.509***	-0.261***
	(0.027)	(0.033)	(0.059)	(0.090)	(0.029)
cohort_dummy	-0.135***	0.170***	0.348***	-0.209***	0.081***
·	(0.027)	(0.033)	(0.073) 📉	(0.070)	(0.028)
			$\overline{}$		
Observations	32,842	26,300	9,309	12,051	41,615
$R^2$	0.927	0.915	0.922	0.855	0.882
Movie FE	Yes	Yes	Yes	Yes	Yes
Days since release FE	Yes	Yes	Yes	Yes	Yes
Year-Week FE	Yes	Yes	Yes	Yes	Yes
Number of movies	589	412	143	220	770

#### Table 8: Cohort Genre subset 1

Robust standard errors in parentheses

\*\*\* p<0.01, \*\* p<0.05, \* p<0.1





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There maybe lost revenue. Is lost revenue retained by consumer or transferred to other film studios ?



Ackermann, Bradley & Cameron (2020)

## Conclusion

#### Recap

- The timing of a good quality release as a random positive shock
- Strong evidence of an average negative impact, e.g. a loss of a fifth of the daily revenue
- Different genres have differentiated effects: Horror, Mystery or Scifi may be enhanced through a cinematic experience; story based movies suffer, e.g. comedy and drama
- Experiential film genres, a good quality movie is **not** an **exact substitute**; instead the appearance of a pirated movie acts as discovery version, thereby increasing the demand for the cinematic experience
- Low-budget movies benefit from the discovery effect

#### Implications

- Film studios could focus their enforcement of piracy on genres that are most affected
- Release strategies could take into account an optimal number of genres studios release (product mix) given piracy, and the timing of releases, given competing films
- Returns to low-budget, story-based films may be highest when released on streaming services
- Importance of quality tiers in piracy -- may also apply to video games, cooperative versus noncooperative video games



