Strategic Attractiveness and Release Decisions for Cultural Goods*

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Abstract

We study how producers of cultural goods can strategically invest in raising the attractiveness of their goods in order to secure the most profitable release dates. In a game-theoretic setting, where two producers choose their investment expenditure before simultaneously setting the release date of their good, we prove that two equilibria are possible: releases are either simultaneous (at the demand peak) or staggered (one producer delays). In the latter equilibrium, the first-mover secures its position by investing more in attractiveness. We test this prediction on a dataset of more than 1500 American movies released in ten countries over 12 years. Results are consistent with the theoretical predictions, indicating that higher budget movies are released closer to seasonal demand peaks.

Keywords: Non-price competition, Strategic timing, Motion pictures.
JEL-Classification: L13, L82

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1 Introduction

In several cultural industries, choosing release dates is a major strategic issue for producers because price competition is limited (if not absent) and demand is seasonal. For instance, in the motion picture industry, movie studios do not seem to compete in prices;[1] as a result, "the movie's release date is one of the main short-run vehicles by which studios compete with each other" (Einav, 2007, p. 127). Clearly, all studios would prefer to have their movies released in periods of large audience (typically, the summer period or the end of the year).

Another example is the market for literary works in France. First, price competition was neutralized in 1981 when a Fixed Book Price law was passed; second, the end-of-year holidays are traditionally the period when book sales culminate; third, the lion's share of novels are released during the 'Rentrée littéraire', a period that spans from late August to early September.[2] Similar patterns can be observed for the release of books in other countries,[3] of video games,[4] and of Franco-Belgian comic books (known as *bandes-dessinées* in French).[5]

The strategic importance of choosing a release date places producers of cultural goods in a configuration that resembles a game of chicken: they all want to release their good at the same dates, and although none of them is willing to yield, they all admit that spacing out releases is preferable. The question that naturally arises is how producers can turn the odds in their favor in this game of chicken.

Product preannouncement may be a strategy.[6] Yet, one can doubt that producers have sufficient commitment power to make such pre-announcements credible. Moreover, if an announcement turns out to be (intentionally or unintentionally) false, the producer's reputation may be damaged.[7] Producers of cultural goods must thus find other means to scare off the competition, so as to secure the most profitable release dates. In this paper, we argue that investments aiming at increasing the attractiveness of the good for consumers do indeed play this role. We develop our argument in a simple game-theoretic model, where two producers of cultural goods make two sequential decisions: they first choose how much to spend in increasing the attractiveness of their good before simultaneously setting the release date.

Assuming that the size of the potential demand decreases with time and that the life cycle of goods has a given length, we show that two equilibrium configurations are possible: either

[1]It is observed that ticket prices are generally uniform and relatively stable over time and across locations (see Orbach and Einav, 2007, and Chisholm and Norman, 2012).

[2]Two reasons drive editors to favor this period; first, they want to initiate positive word-of-mouth for their books before the end-of-year holidays; second, they want to place their books in good order for the various book prizes (e.g., 'Prix Goncourt') that are awarded from September to November (as winning one of these prizes may substantially boost sales).

[3]See Gaffeo *et al.* (2008) for the Italian book market.

[4]Engelstätter and Ward (2016) report that demand peaks when the school period is over, and that video game publishers adjust the release dates of their games to avoid weeks where competition within their niche is strong.

[5]Guilbert (2012) reports that about 60% of major comic books (i.e., those that sell more than 75.000 units) are released between the end of August and early December, which is the time where bookshops decide what will be on their shelves during the busy Christmas period.

[6]For instance, Keyes (2014) reports that "Marvel studios has mapped out films all the way to 2028".

[7]The derisive term 'vaporware' is used to designate such announced products that are released far behind schedule (or never released); Dietz (2011) lists vaporware video games.

both producers release their good immediately (i.e., when demand peaks), or one producer releases its good at the peak while the other producer only releases its good once the life cycle of the first good is over. Interestingly, in the equilibrium with staggered release, the first-mover invests more in attractiveness than the second-mover (whereas in the equilibrium with simultaneous release, both producers invest the same amount). As a larger expenditure allows a producer to 'steal' part of the demand at the rival's expense, we see that investing heavily in attractiveness may allow a producer to credibly secure the most profitable release date for itself. In an extension of the baseline model, we show that this argument also applies in an environment where future attractiveness is uncertain and release dates can be rescheduled. Moreover, our model also allows us to identify a number of factors that make staggered release more likely (and, conversely, simultaneous release less likely). In particular, we expect producers of cultural goods to space out more their releases if their goods are closer substitutes (e.g., because they belong to the same genre), if demand does not decay too fast after the peak, and if investment in attractiveness is less costly.

In the second part of the paper, we bring the predictions of our theoretical model to the data. We first provide anecdotal evidence from the video game and book markets that illustrate the game of chicken that producers play. We then systematically apply our theory to the movie market. Using information from *Box Office Mojo*, we compiled a dataset of more than 1500 American movies released in ten countries over a twelve-year period (from January 1, 2002 to December 31, 2013). For each movie, the data includes the following information: official release date, total box-office revenues, genre, whether it is a sequel or not, studio, and production budget. As the latter variable comprises expenditures such as cast, director, or special effects, we take it as a measure of a studio's investment in raising the attractiveness of its movie. To verify whether movies with bigger budgets tend to be released closer to the demand peaks, we first identify the demand peaks in each season in the various countries. Then, we define our dependent variable as the number of weeks that separates the release date of a movie from the nearest demand peak. As independent variables, we include the budget of the movie, a dummy variable that takes value one if the movie is a sequel of a previously released movie, the sums of the budgets of the other movies released during the same week, distinguishing between movies of the same genre and movies of other genres (the last two variables are meant to measure the influence of competition). We regress this model using an OLS approach, controlling for studio, year, season and country fixed-effects.

Our empirical analysis confirms the predictions of the theoretical model. In particular, we show that movies with larger budgets tend to be released closer to the seasonal peaks. We also find that an increase in the total budgets of competing movies moves the release date closer to the seasonal peak, and that this effect is larger for movies of the same genre than for movies of other genres. A number of robustness checks allow us to establish the validity of these results.

The remainder of the paper is organized as follows. In Section 2, we review the literature and stress the novelty of our contribution. In Section 3, we develop our baseline model, which we extend in Section 4. We then draw a number of hypotheses that we test and discuss in Section 5. We conclude in Section 6.

2 Related literature

Movies are, by far, the cultural goods that have attracted the largest body of academic research, both in economics and in marketing. This is not surprising given the economic importance of the movie industry, the set of interesting issues that it raises (because of its complex production process and its uncertain demand) and the large availability of data sources. The purpose of this section is by no means to review this literature.[8] Our goal here is to show that, despite the extensive research on the movie industry, very few papers have considered the strategic aspect of release decisions and no paper so far (to the best of our knowledge) has dealt with the issue that we study in this paper, namely the interplay between investment and release decisions in a competitive setting.

A busy strand of the empirical literature on movies aims at estimating the demand for movies and the determinants of box-office revenues. Among these determinants, the simultaneous release of similar movies (same genre or same targeted audience) is shown to have a negative effect (see Ainslie *et al.*, 2005, Basuroy *et al.*, 2006, and Calantone *et al.*, 2010). Guttierez-Navratil *et al.* (2014) study to what extent box-office revenues are affected by the temporal distribution of rival films. Using data on movies released in five countries (USA, UK, France, Germany and Spain), they show that the effect of contemporary rivals is always larger than that of previously released movies or future rivals.

In the minority of papers that adopt an industrial organization perspective and explicitly incorporate strategic issues, a number of papers consider release decisions as the main strategic variables. However, the focus is often on the so-called 'release window', i.e., the sequence of release dates of a given movie through different distribution channels (movie theater, on-demand, DVD, cable TV, terrestrial TV). These papers argue that decisions about the release window are mainly driven by three effects: piracy (Danaher and Waldfogel, 2012), word-of-mouth (Moul, 2007) and substitution across versions (Calzada and Valetti, 2012). The analyses of the optimal release window are either purely empirical or, if theoretical, they adopt a monopoly framework. A notable exception is Dalton and Leung (2017), who consider another strategic determinant of the choice of release window, namely the incentive for studios to avoid releasing blockbusters at the same dates.[9]

Only a few papers study, as we do, studios' choice of the premiere release date in a competitive setting. Einav (2010) develops an empirical model to study the movie release date timing game; he finds that released dates are too clustered around big holiday weekends and that box office revenues would increase if distributors shifted some holiday released by one or two weeks. Cabral and Natividad (2016) show, both theoretically and empirically, the importance for a movie's future success of leading the box office during the opening weekend (because being number one induces a greater awareness among potential viewers); although the latter paper does not

[8]We refer the interested reader to the complementary surveys of Eliashberg *et al.* (2006), Hadida (2009), McKenzie (2012), and Kumb *et al.* (2016).

[9]They use a discrete choice release gap decision game model to disentangle the impacts of this strategic effect from the effects of piracy and word-of-mouth. Their results suggest that all three factors have an economically significant impact on distributors' release window decision.

directly consider release decisions, it stresses another reason for which studios are likely to fight to release their movies close to demand peaks.

Closer in spirit to our paper are Krider and Weinberg (1998), and King, King and Reksulak (2017), respectively referred to hereafter as KW and KKR. Let us explain how our approach is novel with respect to theirs. KW consider the competition between two movies in a share attraction framework and conduct an equilibrium analysis of the product introduction timing game (or 'release game'). They show, like we do, that the release game has two potential equilibria: one "with the stronger movie claiming the early release time and the weaker one delaying" and the other one where "both movies [are] more similar (...) [and] open simultaneously at the beginning of the season" (p. 2). They do not explain, however, why movies are more or less strong to start with. Yet, they note on page 5 that "[a]t the point the timing decision must be made, the studios have conducted extensive market research on both their own and the competitions' upcoming releases. A movie's marketability depends on factors that must be highly visible to the potential audience before release. These factors, such as stars, genre, special effects, and prerelease 'hype,' therefore must be equally visible to the competition." That is, the authors recognize that studios do make observable decisions in view of making their movie stronger in terms of marketability (or 'attractiveness' in our vocabulary). Hence, to analyze properly the choice of release dates, we first need to consider how studios invest to determine the attractiveness of their movie, as these investments crucially shape the release game. To this end, we model a two-stage game, where investments in attractiveness precede release date choices. This allows us to provide KW's results with a firmer foundation: a second-stage equilibrium with staggered releases follows asymmetric investments at the first stage, with the firm investing less delaying its release; in contrast, an equilibrium with simultaneous releases follows symmetric (and high) investments. Our setting also generates useful additional results: we can relate the occurrence of these two equilibria to parameters pertaining both to the investment and the competition stage; we also show that a pure-strategy Nash equilibrium may fail to exist, as both firms struggle to find the right balance between the costs and benefits of being strong and of avoiding head-to-head competition. Let us add that our empirical setting is more ambitious, as we test our predictions on a much wider dataset, and we directly estimate how the choice of release date is affected by previous investment decisions (for the movie under review and for contemporary movies), whereas KW use ex post variables, namely the opening weekend and the half-life box office, as proxies for the 'strength' of a movie.

As for KKR, they share with us the empirical finding that budgets are larger for movies released during periods of large audience (exploiting a data set that is richer than ours). However, the theoretical explanation they propose for this result is questionable. Their story is that budget expenditures can signal quality for consumers in an asymmetric information framework, leading to a separating equilibrium where studios with high-quality (resp. low-quality) movies spend larger (resp. smaller) budgets and release them during high-demand (resp. low-demand) periods. In contrast, we believe that a full-information model is more appropriate. Like KW (see the above quote), we note that budget expenditures (related, e.g., to stars or special effects) are highly observable for both the potential audience and the competitors; therefore, they can be used as a commitment device to secure release during the most profitable periods. Now, even if studios conduct extensive market research on the strengths of their own and the competitors' movies, it is true that success remains largely unpredictable. Information is thus incomplete but what matters in terms of modeling is that information remains symmetric, insofar as studios and audience face the same uncertainty. This is why we extend our model by adding uncertainty about a movie's actual attractiveness, as well as the possibility for studios to reschedule release dates, thereby adding another distinctive feature with respect to KW and KKR.[10]

3 A theoretical model of competition in cultural industries

In this section, we present our baseline model, which depicts a two-stage competition between two producers of cultural goods. We first describe the setting and discuss the relevance of our assumptions. Then, proceeding by backward induction, we analyze the (short-term) choice of release dates before turning to the (long-term) investment in attractiveness.

3.1 The setting

Our objective is to build a reasonably simple model that captures what we believe are the main features of several cultural industries: (i) the absence of price competition; (ii) a seasonal and fast-decaying demand; and (iii) intertwined investment and release decisions.

Regarding the first point, we observe that in contrast with most other industries, *price is not the main strategic variable* for cultural goods. As argued in the introduction, this may be due to specific legislations or industry-wide agreements that fix prices (as is common for books in Europe; see, e.g., Ringstad, 2004), or because prices are chosen by third parties in accordance with their own strategic motives (as is the case for movie tickets).[11]

As far as the shape of demand is concerned, *seasonality* plays an important part for many cultural goods. There are periods of the year that are more conducive to consuming cultural goods, because of availability (vacations, holidays), climate (for instance, air-conditioned theaters are more attractive during the hot summer days), or a specific context (such as upcoming

[10]As far as KKR model is concerned, let us add that their results rely heavily on two rather ad hoc assumptions: (i) consumers are more sensitive to quality in high-demand than in low-demand periods; (ii) the profit-enhancing effect of the 'signal' is larger for a studio that has drawn a high-quality vs. low-quality movie, and in high-demand vs. low-demand periods. The authors propose an empirical test for the first assumption, but fail to justify the second. Moreover, whereas they focus on a separating equilibrium (which they take as given), we show the existence of equilibria that can be either 'separating' or 'pooling' (i.e., equilibria with 'staggered' or 'simultaneous' release in our terminology).

[11]Einav (2007, p. 129) explains that the motion picture industry "is dominated by the major studios that have integrated production and distribution", whereas "with few exceptions, exhibitors are not vertically integrated with producers or distributors"(vertical disintegration is even the rule in the U.S. after a series of court orders that were taken in the late 1940s). McKensie (2008, p. 80) explains that exhibitors "have an incentive to hold down (relatively speaking) all ticket prices in order to increase the demand for popcorn (and other concessions)."Hartmann and Gil (2009) establish empirically that exhibitors do indeed 'meter' the surplus that can be extracted from a customer through the quantity of popcorn and other concessions they demand.

awards or prizes).[12] Another characteristic of the demand for cultural goods is that it is usually *short-lived* as consumers have a strong taste for novelties.[13]

The seasonal and transient nature of demand for cultural goods make release decisions highly strategic. Yet, as all producers make the same reasoning and as cultural goods are inherently experience goods, release decisions cannot be decoupled from decisions that affect the attractiveness of the goods. Such decisions include any activity aimed at signaling the quality of the cultural good and/or its potential fit to the tastes of the consumers, and at capturing the attention of consumers; we can think, for instance, at the hiring of famous cast or director or costly special effects for movies, or at higher quality graphics for video games, combined with media advertising and other marketing tools.

The interplay between attractiveness and release decisions lies at the heart of our model. We consider indeed the competition between two cultural goods supplied by two different producers, which compete in two stages.[14] Producers (indexed by $i, j \in \{1, 2\}$) compete in two stages. At period 0, producer i invests an amount a_i to raise the attractiveness of its good; we call a_i producer i's 'investment'; we normalize it to $[0, 1]$ and we assume that it is observable and irreversible (which turns this investment into a commitment). At the end of period 0, after observing the investment of the other producer, producer i chooses the release date of its good, $t_i \geq 1$, where $t_i = 1$ (resp. $t_i > 1$) means that the good is released at the start of (resp. later in) the sales period.[15]

The number of consumers (readers, viewers, or gamers) that a particular good attracts at a particular date depends on: (i) the investments in attractiveness of the two producers; (ii) the number of goods on sales at the same date; (iii) the degree of similarity between the two goods; and (iv) the date itself. Letting $n_i(t, a_i, a_j)$ denote the expected number of consumers for good i at date t given investments (a_i, a_j), we assume:

$$n_i(t, a_i, a_j) = \begin{cases} h(1 + a_i) N t^{-\alpha} & \text{if } i \text{ is the only good on sale,} \\ h(1 + a_i - \beta a_j) N t^{-\alpha} & \text{if both goods are on sale,} \end{cases} \tag{1}$$

with $N > 0$, $h \leq \frac{1}{2}$, $a_i, a_j \in [0, 1]$, $\alpha > 0$ and $0 \leq \beta \leq 1$.

The demand function (1) should be understood as follows. First, the potential audience for

[12] As for movies, the usual demand peaks are the festive season, early May and the summer, with the addition of public holidays (we return in detail on this in Section 5). As discussed in the introduction, the demand for novels, comic books and video games also peaks at the end of the year.

[13] Regarding movies, Einav (2007, p. 129) reports that "the first week accounts for almost 40% of total domestic box-office revenues on average."As for video games, Engelstätter and Ward (2016, p. 3) write that "[s]ales for an individual product are strongest immediately after launch but fall quickly."

[14] In Section 4, we add a third stage to the game; in Section 5.3, we discuss the case where the same producer supplies the two goods.

[15] This sequence of decision corresponds to what is observed in the movie industry: as noted by Vanderhart and Wiggins (2001), the advertising campaign starts before the movie release date and culminates at the time the movie is released. Even if budget decisions might be adjusted through time (and not made once and for all, as we assume here for simplicity), it is the observable cumulated budget expenditure that matters for our purposes. Einav (2002) also notes that studios tend to pre-announce the release date of their movies so as to scare off the competition, and that this practice is more common for movies with larger budgets. This suggests again that budget decisions are made before release decisions and with a view to influence them.

any good at date t is equal to $Nt^{-\alpha}$, where N is the number of consumers (each consumer may buy up to one unit of each good). That is, the audience is the largest at date $t = 1$ (i.e., just after the attractiveness expenditures have been sunk) and then it decreases at rate $\alpha > 0$ per unit of time, as the interest for cultural goods fades away as time goes by. Behind this formulation, there are two simplifying assumptions, which we make to keep the model tractable: first, it is for exogenous reasons that date $t = 1$ is a peak of demand; second, producers cannot release their good before date $t = 1$. We are aware, however, that these assumptions may not square perfectly with the facts: first, demand peaks may be partly endogenous (as demand may increase when popular goods are released); second, releasing a good before a peak may be as efficient as releasing it after a peak when it comes to avoid head-to-head competition. In the empirical part, we explain our strategy to deal with the potential limitations of these two assumptions (see Section 5.2).

Second, each good has an ex ante probability $h \leq \frac{1}{2}$ of being chosen by any consumer. Producer i can increase this ex ante probability by spending more on increasing attractiveness, i.e., by raising a_i. The ex post probability is indeed given by $h\,(1 + a_i)$ when good i is the only one on sale. However, if producer j releases its good in the same period, the ex post probability that consumers will decide to consume good i is given by $h\,(1 + a_i - \beta a_j)$.[16] That is, by investing more in attractiveness (larger a_j), producer j makes it *less* likely that good i will be chosen.[17] The influence of the other producer's investment depends on the degree of similarity (or substitutability) between the two goods, which is parametrized by $\beta \in [0, 1]$. At one extreme, $\beta = 0$ means that the goods are totally differentiated, so that the audience for good i is not affected by the investment of producer j. At the other extreme, $\beta = 1$ means that the goods are perfect substitutes, so that if both producers invest the same amount, they exactly neutralize each other. In the case of movies, an example for the former case could be one teen comedy and one documentary on astrology, while an example of the latter case could be two superhero movies telling similar stories, and having equally popular casts.[18]

We assume that the two cultural goods have the same life cycle (i.e., the period during which they are on sale), which is exogenously set to be equal to $s > 0$.[19] As prices are fixed, we assume that the margin that a producer gets from each purchase of its good is fixed and equal to $m > 0$.

[16] The assumptions that $h \leq 1/2$ and $a_i, a_j \in [0, 1]$ make sure that this ex post probability is positive and lower than one.

[17] We assume thus that initial investments help producers steal each other's audience. Cartier and Liarte (2012, p. 25) provide an illustration in the movie industry: "studios will try to pre-empt the resources necessary for marketing and distributing a film (advertising space, large number of prints made available to theatres, based on the film's potential)."

[18] Under this formulation, if the two goods are on sale, the total number of consumers for the two goods at a given date t is given by $T_t \equiv Nt^{-\alpha}h\,(2 + (1 - \beta)\,(a_i + a_j))$ .When goods are perfect substitutes ($\beta = 1$), $T_t = 2hNt^{-\alpha}$; with $h = 1/2$, we have that $T_t = Nt^{-\alpha}$, meaning that each consumer purchases exactly one good (the relative market share of each good being determined by a_i and a_j). When goods are totally differentiated ($\beta = 0$), $T_t = hNt^{-\alpha}\,(2 + a_i + a_j)$; with $h = 1/2$ and $a_i = a_j = 1$ (maximum investment), we have that $T_t = 2Nt^{-\alpha}$, meaning that all consumers purchase both goods. Our formulation of demand is thus based on the idea that consumers love variety.

[19] For instance, Einav (2007, p. 130) notes that "[t]ypically, a theater screens a movie for six to eight weeks."

Hence, the revenues of producer i at date t is given by

$$R_i\left(t, a_i, a_j\right) = \begin{cases} mhN\left(1+a_i\right)t^{-\alpha} & \text{if } i \text{ is the only good on sale,} \\ mhN\left(1+a_i-\beta a_j\right)t^{-\alpha} & \text{if both goods are on sale.} \end{cases}$$

We see that revenues are scaled by the constant mhN. Without any loss of generality, we can set $mhN = 1$ for the rest of the analysis. For the sake of simplicity, we assume that there is no discounting.[20] We can now express the flow of revenues for producer i as a function of the investments and release dates chosen by the two producers:

$$R_i\left(t_i, t_j\right) = \begin{cases} R_a \equiv \int_{t_i}^{t_i+s}\left(1+a_i\right)\tau^{-\alpha}d\tau \\ \qquad\qquad\qquad \text{if } 1 \leq t_i \leq \max\left\{t_j - s, 1\right\}, \\ R_b \equiv \int_{t_i}^{t_j}\left(1+a_i\right)\tau^{-\alpha}d\tau + \int_{t_j}^{t_i+s}\left(1+a_i-\beta a_j\right)\tau^{-\alpha}d\tau \\ \qquad\qquad\qquad \text{if } \max\left\{t_j - s, 1\right\} \leq t_i \leq t_j, \\ R_c \equiv \int_{t_i}^{t_j+s}\left(1+a_i-\beta a_j\right)\tau^{-\alpha}d\tau + \int_{t_j+s}^{t_i+s}\left(1+a_i\right)\tau^{-\alpha}d\tau \\ \qquad\qquad\qquad \text{if } t_j \leq t_i \leq t_j + s, \\ R_d \equiv \int_{t_i}^{t_i+s}\left(1+a_i\right)\tau^{-\alpha}d\tau \\ \qquad\qquad\qquad \text{if } t_j + s \leq t_i. \end{cases}$$

In segments R_a and R_d, producer i enjoys exclusivity, either because it releases its good sufficiently before (R_a) or sufficiently after (R_d) producer j; note that segment R_a only appears if $t_j > 1 + s$. In segments R_b and R_c, the life cycles of the two goods overlap, with good i being released either before (R_b) or after (R_c) good j.

3.2 Release decision

We now solve the game backwards for its subgame-perfect equilibria. First, we show that only two equilibrium configurations are possible in the second stage: either both producers release their good at the very first date ($t_1^* = t_2^* = 1$) or one producer releases its good immediately while the other producer waits for the end of the life cycle of the first to release its own, i.e., $t_i^* = 1$ and $t_j^* = 1 + s$. We call the former configuration "simultaneous release" and the latter "staggered release".[21] Before stating the result formally, we introduce the following notation:

$$v_1 \equiv \int_1^{1+s}\tau^{-\alpha}d\tau,\ v_s \equiv \int_{1+s}^{1+2s}\tau^{-\alpha}d\tau, \text{ and } \beta_0 \equiv 1 - v_s/v_1.$$

These values should be interpreted as follows: recalling that mNh is set equal to 1, v_1 (resp. v_s) is the expected revenue for a good released at date $t = 1$ (resp. $t = s$) when it is the only one on sale during the whole life cycle and when no investment in attractiveness was made ($a_1 = a_2 = 0$). Naturally, as interest for goods decays over time, we have that $v_1 > v_s$. It is also clear that both v_1 and v_s decrease with α: as demands decays faster, the cumulated audience decreases. Also, the ratio v_s/v_1 decreases with α.[22] As for the threshold β_0, it is the

[20]Somehow, discounting is already included in the decaying interest for goods over time.

[21]Krider and Weinberg (1998) reach a similar result using a different timing game.

[22]Developing the expressions, we have $v_1 = ((1+s)^{1-\alpha} - 1)/(1-\alpha)$ for $\alpha \neq 1$ and $v_1 = \ln(1+s)$ for $\alpha = 1$; $v_s = \left((1+2s)^{1-\alpha} - (1+s)^{1-\alpha}\right)/\left(1-\alpha\right)$ for $\alpha \neq 1$ and $v_s = \ln(1+2s) - \ln(1+s)$ for $\alpha = 1$.

degree of substitutability that leaves a producer that invests nothing in attractiveness ($a_i = 0$) indifferent between staggered and simultaneous release when the other producer releases its good immediately ($t_j = 1$) and invests the maximum in attractiveness ($a_j = 1$); simultaneous (resp. staggered) release is preferred for $\beta <$ (resp. $>$) β_0. In what follows, we assume that $\beta_0 \geq 1/2$ or $v_1 \geq 2v_s$. The reason is twofold: first, this assumption is consistent with the observation that the demand for most cultural goods decays pretty fast;[23] second, as $\beta \leq 1$ by definition, this assumption allows us to exclude the case $\beta > 2\beta_0$, which poses technical issues that are of little interest for our analysis.[24]

The characterization of the second-stage equilibrium is presented in the next proposition and in the two panels of Figure 1. (The proof is mostly technical and relegated to Appendix 7.2.)

Proposition 1. (1) *For* $\beta \leq \beta_0 = 1 - (v_s/v_1)$, $(t_1^*, t_2^*) = (1,1)$ *for all* $a_1, a_2 \in [0,1]^2$. (2) *For* $\beta_0 < \beta \leq 1$, *we have* $(t_1^*(a_1,a_2), t_2^*(a_1,a_2)) \in$

$$\begin{cases} \{(1,1)\} & \text{if } \frac{\beta}{\beta_0}a_2 - 1 \leq a_1 \leq \frac{\beta_0}{\beta}(1+a_2), \\ \{(1,1+s)\} & \text{if } a_1 \geq \frac{\beta_0}{\beta}(1+a_2), \\ \{(1+s,1)\} & \text{if } a_1 \leq \frac{\beta}{\beta_0}a_2 - 1. \end{cases}$$

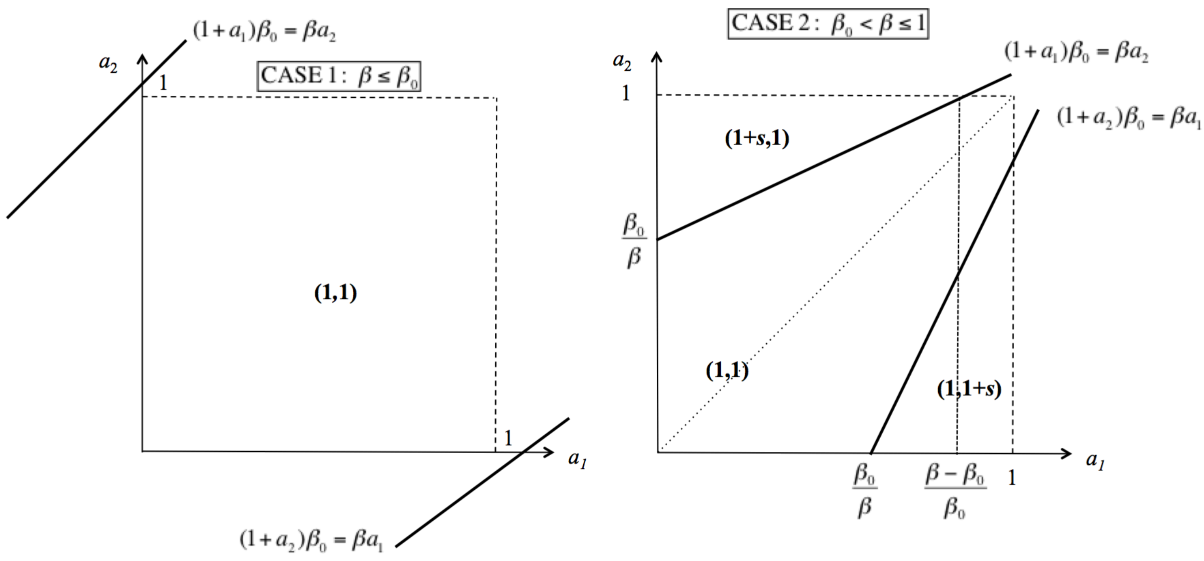

Figure 1: Equilibrium release dates

We see from Proposition 1 and the right panel of Figure 1 that staggered release ($t_i^* = 1$, $t_j^* = 1 + s$) requires two conditions: on the one hand, the two goods must be sufficiently similar ($\beta > \beta_0$) and, on the other hand, the producers must have invested relatively dissimilar amounts.

[23]We show in Appendix 7.1 that this assumption is consistent with the finding that the first week of exploitation of a movie accounts, on average, for almost 40% of the total box-office revenues (Einav, 2007, p. 129).

[24]When $2\beta_0 < \beta \leq 1$, the similarity between the goods is so large that avoiding simultaneous release is the main motivation for both producers, resulting in the coexistence of two symmetric staggered equilibria in pure strategies and one equilibrium in mixed strategies.

To be more precise, a producer may force the rival to postpone the release of its good by investing sufficiently more than its rival. The required difference in investment levels becomes smaller as goods become closer substitutes.

3.3 Investment decision

We now analyze how producers choose their investment in attractiveness, anticipating the equilibrium release dates that will ensue. We assume that investment costs are convex: $C(a_i) = (\gamma/2)\, a_i^2$, where $\gamma > 0$ is an inverse measure of the efficiency of the technology. At this stage, firm i chooses its investment a_i to maximize its profit $\pi_i = R_i - C(a_i)$.

If $\beta \leq \beta_0$, the first stage is extremely simple as a unique equilibrium obtains in the second stage. Firm i maximizes $(1 + a_i - \beta a_j)\, v_1 - (\gamma/2)\, a_i^2$. The optimum is $a_i = v_1/\gamma$. To guarantee $a_i \leq 1$, we assume that $\gamma > v_1$. In the rest of this section, we analyze the case where $\beta_0 < \beta \leq 1$.

3.3.1 Equilibrium with simultaneous release

If simultaneous release is the second-stage equilibrium, the producers choose $a_1 = a_2 = v_1/\gamma$ and their profits are

$$\pi_1^{im} = \pi_2^{im} = \left(1 + (1-\beta)\,\frac{v_1}{\gamma}\right) v_1 - \frac{\gamma}{2}\left(\frac{v_1}{\gamma}\right)^2.$$

Two conditions are needed for this to be a subgame-perfect equilibrium. First, it must be that $(a_1, a_2) = (v_1/\gamma, v_1/\gamma)$ does indeed lead to $(t_1, t_2) = (1, 1)$ in the second stage. We see from Figure 1 that this is always true for $\beta_0 < \beta \leq 1$ as the main diagonal is included in the area where $(t_1, t_2) = (1, 1)$ is the second-stage equilibrium.

The second condition is that no firm finds it profitable to trigger a change of second-stage equilibrium from simultaneous to staggered release. Without loss of generality, consider producer 1. If the second-stage equilibrium is $(1, 1+s)$, then producer 1's maximization program is $\max_{a_1} (1 + a_1)\, v_1 - (\gamma/2)\, a_1^2$. So, the unconstrained optimum is v_1/γ but this value does not satisfy the constraint that must be met to be in the $(1, 1+s)$ zone.[25] So, producer 1 chooses the smallest value of a_1 that meets the constraint, i.e.,

$$a_1^d = \frac{\beta_0}{\beta}\left(1 + \frac{v_1}{\gamma}\right).$$

The corresponding profit is computed as

$$\pi_1^d = \left(1 + \frac{\beta_0}{\beta}\left(1 + \frac{v_1}{\gamma}\right)\right) v_1 - \frac{\gamma}{2}\left(\frac{\beta_0}{\beta}\left(1 + \frac{v_1}{\gamma}\right)\right)^2.$$

Comparing π_1^{im} and π_1^d allows us to state the following result.

Lemma 1. *If $\beta_0 < \beta \leq 1$, the subgame-perfect equilibrium is $(a_1^*, a_2^*; t_1^*, t_2^*) = (v_1/\gamma, v_1/\gamma; 1, 1)$, involving simultaneous release, if and only if*

$$\frac{v_1}{\gamma} \leq \beta_0 \frac{\beta\sqrt{2\beta} - \beta + \beta_0}{\beta^2 (2\beta - 1) + \beta_0 (2\beta - \beta_0)}. \tag{2}$$

[25] We need $\beta a_1 \geq (1 + a_2)\, \beta_0$. With $a_1 = a_2 = v_1/\gamma$, the condition becomes $v_1/\gamma \geq \beta_0/(\beta - \beta_0)$, which is impossible under our assumptions that $\beta < 2\beta_0$ and $v_1/\gamma < 1$.

It is clear that the LHS of condition (2) decreases if v_1 decreases (which can result from an increase in α) or if γ increases. As for the RHS, simple derivations show that it increases if β decreases or if β_0 increases. Recalling that $\beta_0 = 1 - v_s/v_1$, we have that an increase in β_0 is caused by a decrease in the ratio v_s/v_1 (which can itself be caused by an increase in α). We can therefore conclude that an equilibrium with simultaneous release is more likely (i) the larger γ, (ii) the smaller β, and (iii) the larger α. All these results confirm the intuition: (i) if it is more costly to increase the attractiveness of a good (larger γ), forcing the rival to delay the release of its good becomes less profitable; (ii) if goods are less similar (smaller β), being sold at the same time hurts less; (iii) if demand decays faster (larger α), simultaneous release is more attractive even if it implies being sold at the same time.

3.3.2 Equilibrium with staggered release

Suppose that producer 1 releases its good at $t_1 = 1$, and producer 2 at $t_2 = 1 + s$. As long as these release dates are maintained, it is easily seen that the two producers will choose their investment as $(a_1, a_2) = (v_1/\gamma, v_s/\gamma)$, leading to the following profits:

$$\pi_1^{st} = \left(1 + \frac{v_1}{\gamma}\right) v_1 - \frac{\gamma}{2}\left(\frac{v_1}{\gamma}\right)^2, \ \pi_2^{st} = \left(1 + \frac{v_s}{\gamma}\right) v_s - \frac{\gamma}{2}\left(\frac{v_s}{\gamma}\right)^2.$$

For these strategies to be part of a subgame-perfect equilibrium, it must first be the case that the investments $(a_1, a_2) = (v_1/\gamma, v_s/\gamma)$ generate $(1, 1+s)$ as second-stage equilibrium. From Proposition 1, this is so as long as

$$\frac{v_1}{\gamma} \geq \frac{\beta_0}{\beta}\left(1 + \frac{v_s}{\gamma}\right). \tag{3}$$

Second, we must check that no producer has an incentive to choose an investment that would lead to another second-stage equilibrium. It is first easy to show that the producer that releases its good first does not have any profitable deviation. This result is not surprising as releasing its good at date $t = 1$ and facing no competition appears as the best possible scenario. Consider now the producer that releases its good at date $t = 1 + s$ (producer 2 here). Referring to Figure 1, we see that two deviations are theoretically possible: producer 2 can change the equilibrium release dates either to $(1, 1)$ or to $(1 + s, 1)$. However, we show in the appendix that the latter option is never feasible. As for the deviation to $(1, 1)$, we show that it is not only feasible but it can also be profitable. To make this deviation not profitable, condition (4) must be imposed, which is more stringent than condition (3). The next lemma summarizes our results.

Lemma 2. *If $\beta_0 < \beta \leq 1$, the subgame-perfect equilibrium is $(a_i^*, a_j^*; t_i^*, t_j^*) = (v_1/\gamma, v_s/\gamma; 1, 1+s)$, involving staggered release, if and only if*

$$\frac{v_1}{\gamma} \geq \frac{2\beta_0}{\beta_0^2 + 2(\beta - \beta_0)}. \tag{4}$$

In terms of comparative statics, we expect the opposite results than in the previous case: the factors that make staggered release more likely should be those that make simultaneous release less likely. That is, staggered release should be more likely if (i) increasing attractiveness is less costly, (ii) goods are closer substitutes, and (iii) demand does not decay too fast. The first conjecture is clearly verified: if γ decreases, the LHS of condition (4) increases, which makes the condition more likely to be satisfied. The second and third conjectures are also verified.[26]

Combining Lemmata 1 and 2, we can now fully characterize the subgame-perfect equilibrium (in pure strategies) of the two-stage game, where producers choose first an investment in attractiveness and then the release date of their good.

Proposition 2. *The game has two possible subgame-perfect equilibrium (in pure strategies). First, in the simultaneous release equilibrium, both producers invest v_1/γ and release their good immediately; this equilibrium prevails if $\beta \leq \beta_0$ or if $\beta_0 < \beta \leq 1$ and condition (2) is satisfied. Second, in the staggered release equilibrium, one producer invests v_1/γ and releases its good immediately, while the other producer invests $v_s/\gamma < v_1/\gamma$ and releases its good just after the life cycle of the first good is over; this equilibrium prevails if $\beta_0 < 2 - \sqrt{2}$, $(\beta_0/2)(4 - \beta_0) < \beta \leq 1$ and condition (4) is satisfied. Outside these configurations of parameters, a subgame-perfect equilibrium in pure strategies fails to exist.*

Figure 2 illustrates Proposition 2 for $\beta_0 < \beta \leq 1$. It can be shown that the RHS of condition (4) is always larger than the RHS of condition (2), as represented on Figure 2. Hence, a subgame-perfect equilibrium in pure strategies fails to exist for intermediate values of v_1/γ; that is, values of v_1/γ that are too large for simultaneous release to prevail (e.g., because increasing quality is rather cheap, which induces producers to invest more so as to force the other producer to delay), and too small for staggered release to prevail (e.g., because the audience is too condensed at the start of the life cycle). This potential absence of pure-strategy equilibria can be seen as an indication of the instability of competition in cultural goods markets when it comes to choose investments in attractiveness and the timing of release.

4 Model extension: uncertainty and rescheduling

In our baseline model, we made two simplifying assumptions, which we aim to relax in this section. First, we took investments in attractiveness as deterministic; that is, we assumed that firms could predict with certainty by how much their initial investment would expand the demand for their product. This is a big simplification as it is not rare, for instance, that high-budget movies flop at the box office, while low-budget movies are well received by the market. Second, we assumed that producers choose the release date of their good once and for all at the start of the game. This is also a simplification, as it happens in reality that producers modify their initial decision and reschedule the release of their goods. For instance, Einav (2010, p.

[26]As we assume that $\gamma > v_1$, condition (4) can only be satisfied if its RHS is smaller than unity. Some lines of computations establish that two necessary conditions are $\beta_0 < 2 - \sqrt{2} \simeq 0.586$ (which is equivalent to $v_s/v_1 \geq \sqrt{2} - 1 \simeq 0.414$) and $\beta > (\beta_0/2)(4 - \beta_0)$; that is, staggered release can only emerge if demand does not decay too fast and if goods are similar enough. Moreover, one also observes that the RHS of condition (4) decreases with β and increases with β_0, which reinforces the previous findings.

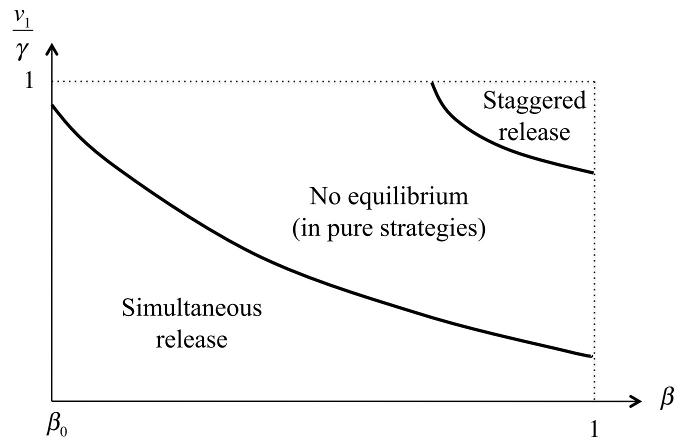

Figure 2: Subgame-perfect equilibrium (in pure strategies)

380) observes that "more than 60% of the movies changed their release dates at least once."[27] Although some of these changes may be due to internal reasons (e.g., unforeseen production delays), it is widely believed that most of them are done for strategic reasons, i.e., as a reaction to current or expected competition. In support for this view, Dürr *et al.* (2017) show that "(1) releases are rescheduled when competition is expected to be stronger, (2) sales decline when competition is stronger, and (3) revenues increase by 7-8% due to weaker competition at the rescheduled date."[28]

To account for these two features, we add a third stage to the game. Stages 1 and 2 are as in the baseline model, with the exception that producers make their investment and release decisions without knowing the exact effect that investments in attractiveness will have on the future demand for their good. In stage 3, uncertainty is lifted and producers have the possibility to reschedule the release of their good. More precisely, we make the following assumptions. We denote by $\tilde{a}_k$ the 'true' attractiveness level of producer k and we suppose that $\tilde{a}_k \equiv a_k + \mu_k$, where μ_k is symmetrically and independently distributed on $[-\mu, \mu]$; that is, the value chosen in stage 1, a_k, is correct in expectation (as the mean of μ_k is zero), but the actual value may end up to be larger or smaller. We also assume that producers can only postpone (and not advance) their date of release, at some cost $\phi > 0$.[29]

Let us analyze the only instance where postponing may be profitable, namely when both producers have announced that they will release their good at date $t = 1$. From our previous analysis, we know that the most profitable postponement is to period $t = 1 + s$. Hence, at stage 3, both producers have two strategies: either maintain release at $t = 1$ or postpone it to $t = 1+s$. Clearly, it is always more profitable not to postpone when the other producer postpones. There

[27] His dataset contains all movies released in the U.S. between 1985 and 1999.

[28] Their dataset contains 1,653 movies released in the U.S. between 2006 and 2014.

[29] We consider only postponements because we want to focus on rescheduling that are made for strategic reasons, i.e., to avoid head-to-head competition (which only happens, in our model, when both goods are released immediately). As for the cost of rescheduling, it can stem from "committed advertising slots, the implicit costs of reoptimizing the advertising campaign, reputational costs, etc" (Einav 2010, p. 380, referring to the movie industry).

are thus three potential Nash equilibria in this game: either both producers maintain, or one of them postpones. Producer i finds it profitable to postpone if and only if the net profit when postponing, $(1+\tilde{a}_i)\,v_s - \phi$, is larger than the profit when maintaining, $(1+\tilde{a}_i - \beta\tilde{a}_j)\,v_1$. Using the definitions of $\tilde{a}_k$ and β_0, we can rewrite the latter condition as

$$\phi \leq \left[\beta a_j - \beta_0\,(1+a_i) - \beta_0\mu_i + \beta\mu_j\right] v_1 \equiv \phi_i\,(a_i, a_j)\,. \tag{5}$$

Defining $\phi_j\,(a_i, a_j)$ in a similar way, we can characterize the Nash equilibrium at stage 3 as follows. If, say, $\phi_i\,(a_i, a_j) < \phi_j\,(a_i, a_j)$, then (i) for $\phi \leq \phi_i$, either producer i or producer j postpones, (ii) for $\phi_i \leq \phi \leq \phi_j$, only producer j postpones, (iii) for $\phi \geq \phi_j$, no producer postpones. Supposing that if two equilibria coexist, each one has the same chance of being selected, we can define $P_i\,(a_i, a_j)$ and $P_j\,(a_i, a_j)$ as the respective probability that producer i or j will postpone the release of its product at the Nash equilibrium of stage 3, given the realizations of μ_i and μ_j. The probability that no producer postpones at equilibrium is then equal to $1 - P_i\,(a_i, a_j) - P_j\,(a_i, a_j)$. It is straightforward from expression (5) that $P_i\,(a_i, a_j)$ decreases with a_i and increases with a_j. It follows that when raising a_i, producer i makes it less likely that it will postpone at stage 3, while making it *more* likely that the other producer will do so.

We are now in a position to express producer i's expected profit in stage 3 when both producers have announced an immediate release at stage 2:

$$\begin{aligned}\pi_i^e\,(a_i, a_j) &= \left[1 - P_i\,(a_i, a_j) - P_j\,(a_i, a_j)\right](1+\tilde{a}_i - \beta\tilde{a}_j)\,v_1 \\ &\quad + P_i\,(a_i, a_j)\left[(1+\tilde{a}_i)\,v_s - \phi\right] + P_j\,(a_i, a_j)\,(1+\tilde{a}_i)\,v_1.\end{aligned}$$

Our goal now is to evaluate how $\pi_i^e\,(a_i, a_j)$ changes with a_i. Noting that $\partial\tilde{a}_i/\partial a_i = 1$ and $\partial\tilde{a}_j/\partial a_i = 0$, and regrouping terms, we have

$$\frac{\partial\pi_i^e\,(a_i, a_j)}{\partial a_i} = \left[(1-P_i)\,v_1 + P_i v_s\right] - \frac{\partial P_i}{\partial a_i}\left[(1+\tilde{a}_i)\,(v_1 - v_s) + \phi\right] + \left(\frac{\partial P_i}{\partial a_i} + \frac{\partial P_j}{\partial a_i}\right)\beta\tilde{a}_j v_1. \tag{6}$$

Let us decompose the latter expression. The first term is the direct positive effect of raising a_i ex ante (and thus raising its ex post value): it increases profit by v_1 if i does not postpone (with probability $1 - P_i$) or by v_s if it does (with probability P_i). The second term shows that raising a_i affects the probability that i postpones and, thereby, faces a smaller audience and incurs the cost of postponing; this term is also positive as $\partial P_i/\partial a_i < 0$: a higher investment at stage 1 decreases the probability that producer i will want to postpone at stage 3 (and will thus incur these two sources of losses). Finally, the third term shows that raising a_i also modifies the total probability to avoid the profit decrease due to the other producer's investment ($\beta\tilde{a}_j v_1$) because either i or j postpones; the sign of this term is a priori ambiguous as $\partial P_j/\partial a_i > 0 > \partial P_i/\partial a_i$. However, expression (5) shows that the effect of a_i on P_i is proportional to $-\beta_0$, while its effect on P_j is proportional to β. We can thus expect to have $\partial P_j/\partial a_i + \partial P_i/\partial a_i > 0$ if $\beta > \beta_0$, i.e., if the two products are sufficiently similar. Otherwise, the third term may be negative but its magnitude will be low as β is small.

The previous elements make us think that $\partial\pi_i^e\,(a_i, a_j)\,/\partial a_i$ should be positive, i.e., that producer i can increase its expected profit at stage 3 by raising its initial investment. Another argument in favor of this result is that a larger initial investment should also be associated with a larger cost of rescheduling. In support of this finding, Einav and Ravid (2009) show that the stock market reacts negatively to information about rescheduling of movies, and that this reaction is greater for movies with higher production costs.[30] Assuming $\phi(a_i)$ with $\phi'(a_i) > 0$ would have two effects on $\partial \pi_i^e(a_i, a_j)/\partial a_i$: on the one hand, P_i would decrease more for a given increase in a_i (as a higher cost of rescheduling decreases the probability that rescheduling takes place), which would increase the weight of the first two terms in expression (6); on the other hand, there would be an additional negative term $(-P_i\phi'(a_i))$. If the former effect is sufficiently strong, it will outweigh the latter and make it even more likely that $\partial \pi_i^e(a_i, a_j)/\partial a_i > 0$. All these findings allow us to safely conclude:

Conclusion 1. *In the presence of uncertainty about the effects of initial investments and when announced release dates can be postponed, increasing the initial investment in attractiveness allows a producer (i) to make it less likely that it will postpone its release date, and more likely that its rival will do so; (ii) to raise its expected profits.*

In a nutshell, uncertainty and rescheduling contribute to strengthen the commitment power of initial investments in attractiveness, which reinforces the conclusion of our baseline model.

5 Empirical analysis

The main testable empirical hypothesis that we can draw from the baseline model and its extension is that producers of cultural goods may decide to invest more in raising the attractiveness of their good as a way to secure release close to demand peaks and discourage their rivals from doing the same. We should therefore observe that:

(H1) *Higher expenditures in attractiveness explain release dates closer to demand peaks.*

The baseline model also shows that the interplay between attractiveness and release decisions strongly depends on the degree of substitutability between the cultural goods: the more similar the goods, the higher the incentive to invest so as to secure the earliest release date, leading to the following hypothesis:

(H2) *The release date of a given cultural good is more sensitive to the expenditures of close competitors (goods of the same genre) than of distant competitors (goods of different genres).*

Third, the baseline model also suggests that producers have the same high expenditures in the simultaneous release equilibrium, while they have different expenditures in the staggered release equilibrium (with the follower spending less). This finding leads us to formulate a third hypothesis:

(H3) *The distribution of expenditures is characterized by both a higher mean and a higher standard deviation in dates closer to a demand peak.*

Finally, the model extension suggests that higher expenditures also serve as a commitment device for not changing the announced release date. We should therefore expect the following:

[30] Rottemberg (2003) also writes: "The bigger a film, the more difficult and expensive it can be to make a midcourse correction."

(H4) *Cultural goods with larger expenditures are less likely to have their release date modified.*

In this section, we bring these predictions to the data. There is ample anecdotal evidence that producers of substitutable cultural goods play a game of chicken in terms of release dates. For instance, the two heavyweights of popular French fiction, Guillaume Musso and Marc Levy, publish their yearly delivery around the same period (February-March) but always at a few weeks' interval (alternating whoever releases first or second).[31]

In the video game industry, casual observation suggests that although releases are concentrated over a few months, it is quite uncommon that games belonging to the same genre be released in the exact same week. For the sake of illustration, we looked at the 70 top-selling PlayStation 4 games of 2015 (according to `www.vgchartz.com`). We note first a strong seasonality: the two months of September and October account for about 40% of the releases. Figure 3 depicts the week of release of the 70 games classified in six genres (from bottom to top: Action, Shooter, Racing, Role playing, Sports, and Others). We see that simultaneous release of same-genre games occurs eight times, for a total of 19 games.[32]

As for movies, the big Hollywood studios have increasingly chosen to release their would-be blockbusters in the US during the summer period (starting Memorial Day weekend, at the end of May), when a bigger audience is available (because kids are out of school, adults are on vacation, and heat waves drive them all inside air-conditioned theaters). This trend culminated in the summer of 2013 with the release of 31 movies aiming at a large audience. As an important number of these 31 movies flopped, some studios decided to make summer 2014 start earlier: Walt Disney, 21st Century Fox and Time Warner made their potential blockbuster debut in April.[33] They may have been inspired by some previous successful releases that took place outside the summer months.[34]

These narratives, however, fall short of clarifying what drove some producers, but not others, to chicken out. To investigate this issue and test whether our theory makes sense, we focus on the movie industry. This choice is entirely motivated by data availability. In the rest of this section, we first describe the data that we use to perform our empirical analysis; we then present our empirical strategy and describe our results; finally, we discuss our results.

[31] See "Guillaume Musso et Marc Levy : la guerre continue ", Le Point, December 23, 2015, available at `http://bit.ly/1YZg7KY`.

[32] This is represented by the colored dots on the figure: a red dot corresponds to two simultaneous releases, a green dot to three, and an orange dot to four. The latter case deserves some explanations. Between September 25th and 29th, the following four sports games were released: *Madden NFL 16*, *NBA Live 16*, *NBA 2K 16*, and *Tony Hawk's Pro Skater 5*. However, it seems hard to argue that these four games were in fierce competition with all the others. First, the fourth game belongs to another category than the first three; second, the first two games were released by the same publisher (Electronic Arts); finally, the two NBA games sold very different numbers of units: 3,56 millions of units for *NBA 2K 16* and 0,16 for *NBA Live 16* (global sales from 29/09/15 to 16/06/2016; source: `www.vgchartz.com`).

[33] Respectively *Captain America: The Winter Soldier*, *Rio 2*, and *Transcendence*.

[34] E.g., *The Hunger Games* (March 2012), *Gravity* (October 2013), or *The Lego Movie* (February 2014).

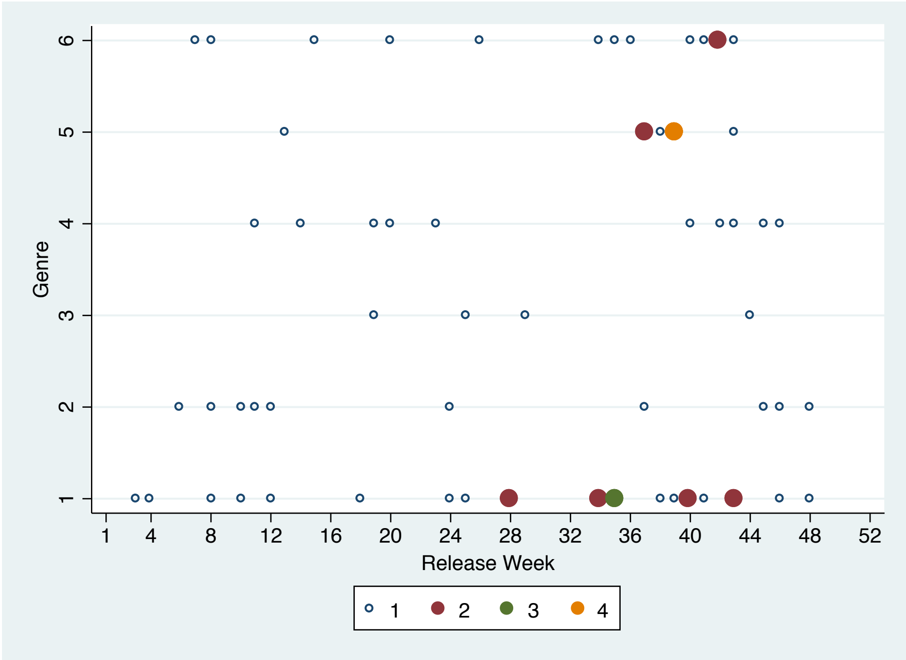

Figure 3: Release dates of top-selling PlayStation 4 games of 2015

5.1 Data

The data (collected on the website *Box Office Mojo*) refers to American movies released in ten countries[35] between January 1, 2002 and December 31, 2013 for which production budgets are available. Our final database comprises 1564 movies and 12904 valid observations (see Table 2 below). For each of the 1564 movies, we know (i) the production budget, (ii) the official release dates (for the countries where the movie was released), (iii) the genre to which the movie belongs, (iv) whether or not the movie is a sequel of (a) previous movie(s), and (v) the studio producing and distributing the movie.

Three comments are in order regarding the data. First, the "production budget refers to the cost to make the movie and it does not include marketing or other expenditures."[36] Unfortunately, broadly available measures of movies' advertising expenditures are hard to find. The absence of such data can be seen as a limitation to test our hypotheses. In our model, we consider indeed budgets as instruments to attract more viewers and, arguably, the main channel to do so is to increase marketing and advertising expenditures. However, we see three reasons as to why production budgets are a reasonable proxy for our purposes. First, they comprise expenditures (such as cast, director, special effects) that are as relevant as marketing expenditures to increase the expected viewership of a movie. Second, compared to advertising expenditures, these expenditures are made earlier, are more easily observable, and are harder to reverse; they provide thus producers with a stronger commitment power in view of influencing the choice of release dates

[35] Australia, France, Germany, Italy, Japan, New Zealand, South Africa, Spain, USA/Canada, and United Kingdom.

[36] See `www.boxofficemojo.com/about/boxoffice.htm`.

(which is the core of our argument). Finally, it is generally estimated that marketing budgets tend to represent a constant proportion (about 50%) of production budgets.[37]

Second, to form sub-samples of relatively comparable sizes, we have grouped movies in five main "genres", namely *Drama*, *Action*, *Suspense*, *Comedy*, and *Other*.[38]

Third, we construct eight binary variables to control for movie studios (i.e., the seven major film studios and a composite variable, named *Others* that comprises the smaller distributors).[39]

Tables 1 and 2 provide some descriptive statistics of the major variables. In Table 1, we report the main characteristics of the 1546 movies in our sample. The mean and standard deviation of the (inflation-adjusted) production budgets are \$54.4 million and \$53.1 million, respectively. Comparing movie genres, we observe that movies in the Action category present the highest mean and standard deviation for the production budgets. We also observe in Table 2 that the market for American movies varies in size across countries. Only a little more than 50% of the American movies in our sample are released in Japan, while this proportion is at least as large as 73% in the other countries. Interestingly, the average production budget is larger for movies released outside the U.S and Canada, suggesting that studios choose not to release small-budget movies abroad (probably because they fear that they will not be profitable enough).

Casual observation of our data lends credence to our hypotheses, as illustrated by Figure 4. This figure plots release dates (on the horizontal axis) against production budgets (on the vertical axis) for movies released in the US/Canada in 2008; each dot corresponds to one movie and the color of the dots indicates to which genre the movie belongs; the vertical lines correspond to the seasonal peaks. We observe that the movies with the larger budgets are indeed released close to the peaks; we also see that when several movies are released close to a peak, they usually belong to different genres and have different budgets (the dots have different colors and are scattered).

5.2 Specification and results

In the theoretical model of Section 3, we assumed for simplicity that everything was starting at some date $t = 1$, corresponding to a peak in demand. In this context, we modeled the trade-off facing studios as choosing between meeting the demand (i.e., immediate release) and avoiding head-to-head competition (i.e., delayed release). In reality (as illustrated in the beginning of this

[37] According to The Motion Picture Association (2003), quoted by Hanson and Xiang (2011, p. 21), "for the average US movie in 2003 65% of total costs were due to film production and 35% were due to marketing, which includes making film prints; advertising on radio, TV, newspapers and other media; and promotional activities."See also `http://en.wikipedia.org/wiki/Film\_promotion` or `http://entertainment.howstuffworks.com/movie-cost1.htm`.

[38] *Drama* corresponds to Mojo category 'Drama', *Action* merges Mojo categories 'Action', 'Adventure', and 'Western', *Suspense* merges 'Thriller/Suspense' and 'Horror', *Comedy* merges 'Comedy', 'Romantic Comedy', 'Black Comedy' and 'Cartoons', and *Other* merges 'Musical, 'Documentary', and 'Concert/Performance'.

[39] *Box Office Mojo* reports the following market shares (in box office revenues) for 2013: Warner Bros. (17.1%), Walt Disney (15.7%), Universal (13.1%), Sony/Columbia (10.5%), Lions Gate (9.8%), 20th Century Fox (9.7%), Paramount (8.8%), and others (15.3%)

		Obs	%	Mean	Std. Dev.	Min	Max
Genre	Drama	378	25	30.6	29.3	0.17 (Once)	206.34 (A Christmas Carol)
	Action	417	25	100.9	66.3	4.85 (Night Watch)	336.9 (Pirates of the Caribbean 3)
	Suspense	262	17	36	31.7	0.16 (Paranormal Activity)	170.88 (Inception)
	Comedy	463	29	45.4	38.4	0.19 (Tadpole)	200 (Monsters University)
	Others	44	4	23.5	28.3	0.08 (Super Size me)	96.12 (The Nutcracker)
Studio	Fox	194	12	51.9	47.7	0.17 (Once)	257.4 (Avatar)
	Liongate	113	7	28.7	27.8	0.32 (Lovely and Amazing)	132 (The Twilight Saga 4)
	Others	218	14	25.1	26	0.08 (Super Size Me)	183.9 (Die Another Day)
	Paramount	171	11	70.1	54.7	0.16 (Paranormal Activity)	228 (Transformers 2)
	Sony	263	17	52.4	50.3	0.46 (Quinceanera)	289.7 (Spider-Man 3)
	Universal	196	13	58.3	49.2	.52 (Brick)	246.9 (King Kong (2005))
	Walt-Disney	177	11	72.7	69.8	0.19 (Tadpole)	336.9 (Pirates of the Caribbean 3)
	Warner	232	15	70.3	59.45	2.46 (Before Sunset)	271.5 (Harry Potter 6)
Sequel		194	12	95.9	73.6	2.46 (Before Sunset)	336.9 (Pirates of the Caribbean 3)
Titles		1564	100	54.4	53.1	0.08 (Super Size me)	336.9 (Pirates of the Caribbean 3)

Table 1: Production budgets per genre and per studio

section), there is another way to avoid competition, which is to release a movie *before* the peak. Including this possibility in our empirical model forces us to address the following question: from a studio's perspective, is it more desirable to release a movie before or after the demand peak? The answer to this question is tricky. On the one hand, the advantage of releasing a movie before the peak is that it will still be on screen when the demand is the highest (even if the attractiveness of the movie itself will have faded). Yet, the downside is that total demand may be much lower before than after the peak (this is typically what happens in the US around the peak of the 4th of July: demand at the end of June is very weak, while it remains very strong in the first weeks of July). Looking at our sample, it seems that these two forces balance out: 40% of movies were released before the nearest peak and 44% after (the remaining 16% were released on the peak).

Even if the latter figures are ex post realizations, we do not have any indication that ex ante (i.e., conditioning on a fixed competitive environment), studios would always prefer releasing their movies x weeks before rather than x weeks after a given peak (or the opposite). Accordingly, we decide to treat the two possibilities in a symmetric way; that is, we define our dependent variable as the *number of weeks (in absolute value) between the release date of a movie and the closest demand peak*:

$$t_{ik} = min\left|peakweek_k - releaseweek_{i,k}\right|,$$

where i identifies the movie and k the country. We show below (in 5.2.3) that our results are robust to asymmetric definitions of t_{ik}.

5.2.1 Seasonal peaks

We identify the seasonal peaks in the demand for movies in the various countries using the following three-step procedure. First, following Mojo, we consider five seasons: Winter, Spring,

Country	Obs	% wrt titles	Average budget	Std. Dev.
US / Canada	1564	100%	54.4	53.1
Australia	1374	88%	58.7	55.5
France	1316	84%	60,0	55.3
Germany	1337	85%	59.7	55,0
Italy	1308	84%	60.1	55.2
Japan	798	51%	78.8	60,0
N. Zealand	1223	78%	61.8	56.4
S. Africa	1152	74%	64.2	56.5
Spain	1401	90%	58.2	54.3
UK	1431	91%	56.9	54.2
Total	12904			

Table 2: Production budgets per country of release

Summer, Fall, and the Holiday Season.[40] Second, we use the weekly box office revenue data in each country to find the share of each week's revenues in the total annual revenues. Third, we define a peak as a week that reaches a sum of box-office revenues that is above the 70th percentile of the seasonal distribution. Table 4 in Appendix 7.6 reports the weeks identified as peaks (by season and by country); note that it is not rare that two or three consecutive weeks qualify as peaks.

One may object that this procedure raises an endogeneity issue for our estimations, as shares are equilibrium outcomes that depend both on demand and supply behavior. Take for instance the summer period. Two reasons may explain why box-office revenues are higher during this period: people may be more willing to go to the movies because they are on vacation or long for air-conditioning (demand effect) and/or because it is precisely the period when studios have decided to release their more popular movies (supply effect). In other words, it may not be clear whether it is the box-office revenue that drives the choice of release dates, or the other way round. Yet, we have several reasons to believe that endogeneity is not a concern for the issue that we study. First, previous research has shown that the demand effect is twice as large as the supply effect.[41] Second, if and when a supply effect exists, it stems from the *combined* release of several popular movies at a given date. In other words, a single movie, however attractive it can be, cannot transform its release date into a seasonal peak by its own forces. As a result, and because studios choose the release dates of their movie independently, their choices cannot be driven by some potential supply effect: the dates that studios see as more profitable are precisely those that are known for drawing more people to the movies, i.e., the dates exhibiting

[40] *Winter* goes from the first day after New Year's week or weekend through the Thursday before the first Friday in March; *Spring* goes from the first Friday in March through the Thursday before the first Friday in May; *Summer* goes from the first Friday in May through USA Labor Day Weekend; *Fall* goes from the day after USA Labor Day Weekend through the Thursday before the first Friday in November; the *Holiday Season* goes from the first Friday in November through New Year's week or weekend.

[41] Einav (2007) disentangles the endogeneity implicit in the data for the US movie market and finds that the behavior of demand accounts for about two-thirds of the seasonal variation in total sales. Cartier and Liarte (2012) perform a similar exercise. Hand and Judge (2011) find the same evidence for the UK market.

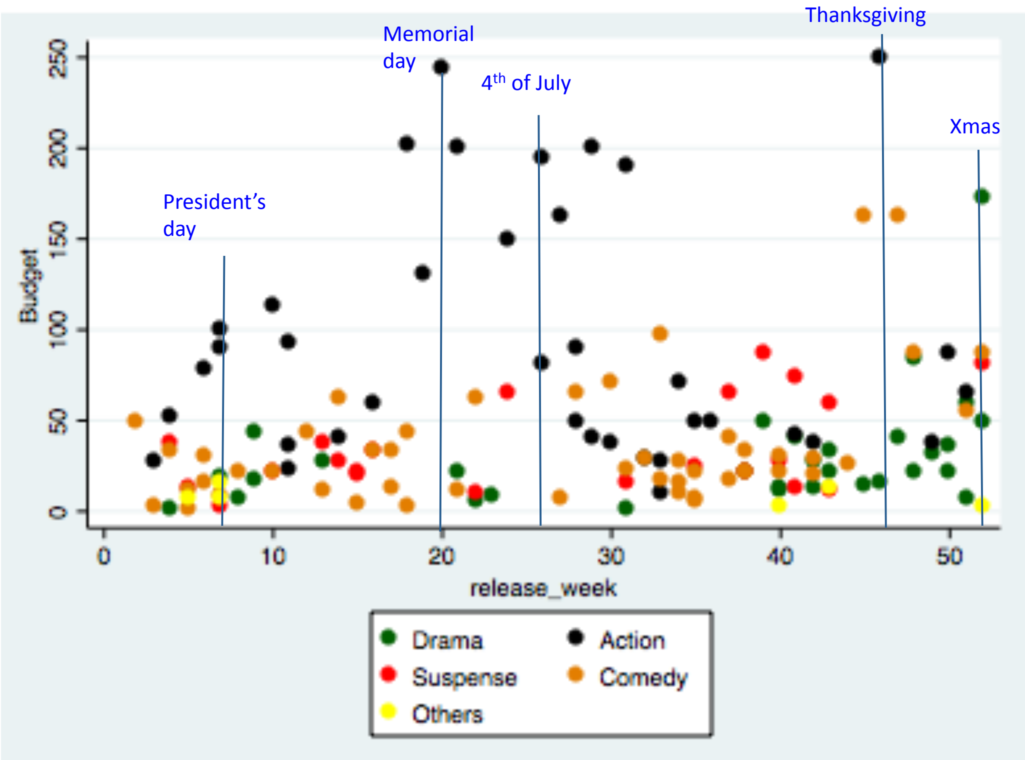

Figure 4: Budgets per week and per genre (USA, 2008)

important demand effects. Third, it is reassuring that the peaks we identify correspond not only to the pattern of movie sales that Einav finds for US/Canada (Figure 4, p. 139, 2007), or Hand and Judge find for the UK (Figure 2, p. 83, 2011), but also to the dates that the conventional wisdom associates with high movie demand (e.g., for the U.S., the major holiday weekends of Presidents Day, Memorial Day, Fourth of July, Thanksgiving and Christmas; see Figure 7 in Appendix 7.6).

5.2.2 Test of hypotheses (H1) and (H2)

To estimate the effects of production budgets and competition on the release date of a movie, we estimate the following specification:

$$t_{ik} = \alpha_k + \beta_1 budget_i + \beta_2 n_{ik} + \beta_3 m_{ik} + \beta_4 sequel_i + \beta_5 X_{i,k} + \varepsilon_{ik}, \tag{7}$$

where the indices i and k refer, respectively, to movies ($i = 1 \ldots 1564$) and countries ($k = 1 \ldots 10$), α_k is a country fixed effect, $budget_i$ is the production budget of film i, n_{ik} (resp. m_{ik}) is the sum of the production budgets of other movies of the same (resp. a different) genre as movie i and released during the the same week as movie i in country k, $sequel_{ik}$ is a dummy variable that takes value one if movie i is a sequel of a previously released movie, and $X_{i,k}$ is a matrix of controls (season, year, and studio). The variable $sequel_{ik}$ is meant to capture the fact that sequels benefit from the popularity acquired by the previous movies in the same series, which may scare off the competition by itself, regardless of the size of the production budget.

Recalling that a *decrease* in t_{ik} means that the release date moves *closer* to the nearest peak, the theoretical prediction stated in hypothesis (H1) leads us to expect a negative value for β_1 (a higher budget is used as a commitment to release near a demand peak, implying a smaller t_{ik}), and negative values for β_2 and β_3 (an increase in the total budgets of contemporaneous movies is taken as a proxy for an increase in the competitive pressure, which should lead the studio to release the movie closer to the peak, i.e., to a smaller t_{ik}). Moreover, according to hypothesis (H2), we should observe $|\beta_2| > |\beta_3|$, as the competitive pressure stemming from movies of the same genre should be felt more strongly.

We report the results of the OLS estimation of specification (7) in the first two columns of Table 3, with the variables n_{ik} and m_{ik} being excluded in Column (2). We see that the estimated coefficient of $budget_i$ has the expected negative sign in both specifications; the estimated coefficients of n_{ik} and m_{ik} also have the expected sign in specification (2); moreover, all coefficients are statistically significant at the 1% level. We also observe in the first specification that $|\beta_2| > |\beta_3|$; that is, the aggregate budgets of movies in the same genre (n_{ik}) exert a stronger effect on the release date of a given movie, compared to the aggregate budgets of all the other movies (m_{ik}). A t-test conducted between the two variables confirms that the difference is statistically different from zero at the 1% level. We can thus safely say that hypotheses (H1) and (H2) are verified.

Noteworthy is the fact that the coefficient of the variable $sequel_{ik}$ is never significant. We interpret this finding as follows: even if sequel movies may benefit from a head start in terms of popularity, releasing them near demand peaks still requires studios to increase their production budgets.[42]

5.2.3 Robustness checks

We check the robustness of our results in various ways. First, it could be argued that production budgets may be a proxy for studios' size and/or reputation. This could be a concern for our analysis insofar as size and reputation (which are omitted from the regression model) could affect both studios' ability to release movies closer to demand peaks and the way studios set production budgets. Another argument could be that the largest studios strive to release movies around demand peaks every year so as to assert their presence on the market, irrespective of the movies' budgets. It is to assess this possibility that we have introduced eight binary variables to control for movie studios in our regressions. It turns out that the effects of these controls are not significant, which leads us to think that they have no impact on the dependent variable.[43]

Second, we propose a Poisson regression model (Maddala, 1983). Poisson distributed data is intrinsically integer-valued, which makes sense for count data as in our case. Since the dependent variable has a restricted support, OLS regression could predict values that are negative and non-integer values, which have no sense. Furthermore, OLS assumes that true values are normally

[42]We observe in Table 1 that sequel movies are characterized by rather large budgets: the mean budget for sequel movies is \$95.9 million, whereas the mean budget for all movies in our sample is \$54.4 million.

[43]We also run our main OLS regression after dropping the group of small studios; we did not observe any significant change in our results.

	(1) OLS	(2) OLS (no n_ik, m_ik)	(3) Poisson	(4) OLS (yearly peaks)	(5) OLS (USA)	(6) OLS (no outliers)	(7) OLS (asym)	(8) OLS (Log Budget)
Budget	-0.0031 ***	-0.0025 ***	-0.0012 ***	-0.0067 ***	-0.0042**	-0.00322***	-0.00491 ***	-0.983***
	(-6.78)	(54.28)	(-6.71)	(-8.56)	(-3.33)	(-6.41)	(-5.96)	(-4.63)
n_ik	-0.0029 ***		-0.0012 ***	-0.0065 ***	-0.0024*	-0.0029***	-0.005 ***	-0.186***
	(-6.30)		(-5.82)	(-8.35)	(-2.38)	(-6.39)	(-6.37)	(-4.38)
m_ik	-0.0026 ***		-0.001 ***	-0.0055 ***	-0.003 ***	-0.0027***	-0.004 ***	-0.008***
	(-10.33)		(-8.99)	(-12.09)	(-5.55)	(-10.42)	(-9.15)	(-3.15)
Sequel	-0.0033	0.0035	-0.011	-0.044	0.078	-0.0413	0.00047	-0.055
	(-0.52)	(-0.06)	(-5.82)	(0.41)	(0.55)	(-0.65)	(0.00)	(-0.89)
Drama	0.159 **	0.158 **	0.64 **	-0.494 ***	0.54	0.16 **	0.428 **	0.144**
	(2.73)	(2.70)	(2.92)	(-5.00)	(0.42)	(2.74)	(4.18)	(2.45)
Action	0.336	0.535	0.176	0.107	-0.244 *	0.0384	0.1	-0.013
	(0.57)	(0.91)	(0.77)	(1.04)	(-1.86)	(0.65)	(1.00)	(-0.23)
Suspense	0.252 ***	0.303 ***	0.092 ***	0.97	-0.85	0.252 ***	0.517 ***	0.272***
	(3.91)	(4.72)	(4.01)	(0.89)	(-0.62)	(3.91)	(4.57)	(4.17)
Others	-0.844	-0.12	-0.32	0.399 *	-0.46 **	-0.0848	0.687	-0.185
	(-0.68)	(-0.97)	(-0.66)	(1.80)	(-1.99)	(-0.68)	(0.31)	(-1.46)
Comedy	(omitted)	(omitted)	(omitted)	(omitted)	(omitted)	(omitted)	(omitted)	(omitted)
Constant	2.646 ***	2.46 ***	0.939 ***	4.99 ***	3.389 ***	2.653 ***	3.512 ***	3.01***
	(25.49)	(22.94)	(21.173)	(31.07)	(11.54)	(25.37)	(19.90)	(15.41)
Controls (season, year, studio)	YES	YES	YES	YES	YES	YES	YES	YES
Country Fixed Effects	YES	YES		YES		YES	YES	YES
R-squared	0.1054	0.0965		0.1058	0.3174	0.1051	0.0911	0.098
Adj R-squared	0.1031	0.0944		0.1039	0.3072	0.109	0.0889	0.095
Pseudo R-squared			0.0248					
Prob > chi2			0.000					
Number of observations	12904	12904	12904	12904	1564	12744	12904	12904

* $0.05 < p < 0.1$; ** $0.01 < p < 0.05$; *** $p < 0.01$

Table 3: Estimation results

distributed around the expected value. So, Poisson regression models perform better in far from normal distributed data. We present the results of this estimation in the third column of Table 3. We observe that the Poisson regression of Column (3) and the OLS regression of Column (1) give very similar results.

As a third robustness check, we modified our dependent variable by identifying demand peaks in a different way: a week is now defined as a peak if it reaches a sum of box-office revenues that is above the 70th percentile of the distribution of a given *year* instead of a given *season*. This changes the distribution of peaks in two conflicting ways: when compared over a whole year, some 'big' weeks within 'small' seasons go out (e.g., in the spring), whereas some 'big' weeks within 'big' seasons come in (e.g., in the summer). These changes are depicted for each country in Table 5 in Appendix 7.6. We regress the newly defined dependent variable over the same set of independent variables as in specification (7). The results are reported in the fourth column of Table 3. We observe that all the coefficients of interest continue to have the expected sign and remain highly significant. The relationship between budgets and release dates seems thus to exist irrespective of the way we define the demand peaks. This suggests that studios compete in terms of release dates not only within each season but also over the whole year.

Fourth, we ran the OLS regression only for the US to control for the possibility that the release date in other countries could be a function of the viewership (or profits) in the US given the release date chosen there. Apparently, this is not so as the results in Column (5) of Table 3 are qualitatively similar to those reported in Column (1). We also repeated our main OLS regression after winsorizing our data (we dropped the movies corresponding to the lowest 5% and highest 5% in the budget distribution); the estimated coefficients, reported in Column (6) of Table 3, are qualitatively similar to those reported in Column (1), which indicates that our results are not driven by outliers.

Fifth, we have explored alternative definitions of our dependent variable to account for the possibility that studios may prefer releasing movies before rather than after a peak. If we understand the distance from a peak in terms of profitability, this would mean that a movie released x weeks after a peak is more 'distant' than a movie released x weeks before the peak. We have thus redefined t_{ik} as follows: if $releaseweek_{i,k} \leq peakweek_k$ (i.e., if movie i in country k is released before or at the nearest peak), then $t_{ik} = peakweek_k - releaseweek_{i,k}$; otherwise, $t_{ik} = \mu(releaseweek_{i,k} - peakweek_k)$, with $\mu > 1$. In Column (7) of Table 3, we report the results of an OLS regression using this alternative definition of t_{ik} with $\mu = 2$. We observe that at the exception of the variable *sequel*, all estimated coefficients are statistically significant at the 1% level, and are similar to the ones we observe in Column (1) with the symmetric definition of t_{ik}. As the same goes when running the regression for other values of μ, we can safely conclude that our results are robust to alternative definitions of our dependent variable, which would account for potential differences in the profitability of releasing movies before or after a peak.[44]

Finally, given that the budget is not normally distributed, we have taken the log of the variables $budget_i$, n_{ik}, and m_{ik}. The results appear in Column (8) of Table 3; they are qualitatively identical to the results of Column (1).

Noteworthy is the fact that all our regressions exhibit rather low values of R^2. The explanation can possibly be found in our theoretical model. Recall from Proposition 2 (and Figure 2) that there exist configurations of parameters for which a pure-strategy Nash equilibrium fails to exist. This indicates that the two-stage competition that takes place in movie markets is unstable, with studios struggling to find the right balance between the pros and cons of being strong and of avoiding head-to-head competition. Our model therefore predicts that studios may often resort to mixed strategies when choosing the combination of budgets and release dates. This randomization inevitably blurs the link between budgets and release dates, which could explain the relatively low proportion of the variation in the dependent variable that is predictable from our independent variables.

[44] As an additional check, we split our sample into two sub-samples according to whether movies were released before or after the nearest peak. We obtained qualitatively similar results for the separate OLS regressions that we ran on the two sub-samples.

5.2.4 Test of hypothesis (H3)

As suggested in Figure 4, the distribution of movie budgets seems to vary a lot week per week. In particular, for weeks at or near a demand peak, the largest budget is higher and the distribution is more dispersed. This observation is consistent with the predictions of our model: higher budgets allow studios to release their movies closer to a peak and to scare off the competition. It is thus unlikely to observe two movies with high budgets released around a peak (especially if they belong to the same genre). As a result, movies coexisting in weeks near a peak should have very dissimilar budgets (very high or very low). Conversely, in weeks further away from peaks, the distribution of budgets should be more concentrated and with a lower mean.

To check this hypothesis, we have categorized movies (across countries and years) according to the number of weeks that separate their release from the nearest peak. We have then computed the mean and the standard deviation of the production budgets for the movies within each category. To verify hypothesis (H3), we should observe that both the mean and the standard deviation decrease as we move to categories of movies that are more distant from a peak.

Figure 5 plots the mean of the standard deviation of the production budgets (vertical axis) against the number of weeks separating the release date from the nearest peak (horizontal axis); the latter variable takes values from 0 to 9. As expected, we observe that both variables decrease as movies are released further from a peak. This observation suggests that hypothesis (H3) is verified.

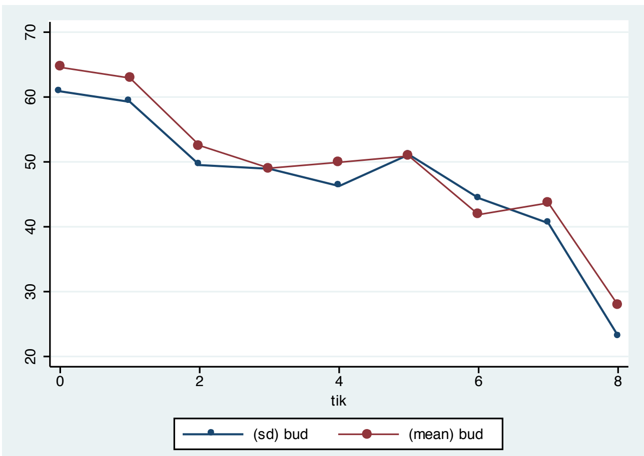

Figure 5: Mean and standard deviation of budgets according to release date

5.2.5 Test of hypothesis (H4)

To examine the link between production budgets and rescheduling, we have complemented our database with data about changes of release dates. Our dataset comprises 746 movies released in the US between late August 2006 and early January 2014; for these movies, we thus have the additional information about their *announced* release date.[45] From this sample, we have eliminated 61 movies whose release date had been postponed by more than 100 days; it seems indeed reasonable to assume that these movies were rescheduled because of some technical or financial problem, and not for strategic reasons. Out of the 685 remaining movies, 511 were released at the initially announced date, and 30 were rescheduled by only a couple of days; that is, the distance to the peak (in weeks) remained unchanged for 79% of our sample (541 movies). For the other movies, the release date was either advanced (65 movies, or 9,5% of our sample) or postponed (79 movies, or 11,5% of our sample).

A first finding is that rescheduling appears as a minor phenomenon in the period that we consider. A second important finding is that production budgets are higher on average for movies whose release date was maintained ($59.72 million) than for those whose release date was advanced ($54.42 million) or postponed ($52.67 million). This finding gives an indirect validation of hypothesis H4, as the probability of changing release dates appears as negatively correlated with the production budget.[46]

5.3 Discussion

We discuss here a number of concerns that our approach could raise. We also indicate how we have already addressed some of them and how we plan to address others in future work.

Movies released by the same studio. Major film studios typically release about 15 to 20 movies per year. Inevitably, several movies are then released within a given season, and these movies may be of the same genre and have similar budgets. This is illustrated on Figure 6, which depicts the movies that 20th Century Fox released in the U.S. in 2008 (weeks are reported on the horizontal axis and genres on the vertical axis; the size of a dot is proportional to the size of the budget of the corresponding movie).

Clearly, studios can only gain by coordinating the budget and release decisions for their movies.[47] We need thus to assess how this possibility affects our analysis. From a theoretical viewpoint, we can analyze the promotion and release decisions of a monopoly studio that produces and distributes two movies, and compare the results to the ones that we obtained in the duopoly model of Section 3. In Appendix 7.5, we show that simultaneous release emerges

[45] We are extremely grateful to Niklas Dürr, who kindly provided us with the data he collected through the Internet archive of Box Office Mojo. Note that Box Office Mojo often fails to mention the exact planned release dates (a typical entry would be *Spring 2014* instead of a precise date). As we analyze the way studios choose the week (and not the season) at which they schedule (or re-schedule) the release of their movie, we cannot infer any information from such imprecise dates. Therefore, we counted only release date changes where the initially planned and actual release dates were exactly known. As a result, the rate of rescheduling that we observe in our sample is inferior to the estimations that were proposed in other papers; for instance, Einav (2010) mentions a rate of rescheduling equal to 60% in his sample.

[46] However, in the various empirical specifications that we tested, the production budget had no significant impact on the probability of rescheduling movies. Dürr *et al.* (2017) obtain a similar result, which can be attributed to the following two facts: only 21% of movies in our sample were rescheduled, and other non-strategic reasons may induce studios to modify release dates.

[47] Meisner (2016) empirically shows that it is indeed the case.

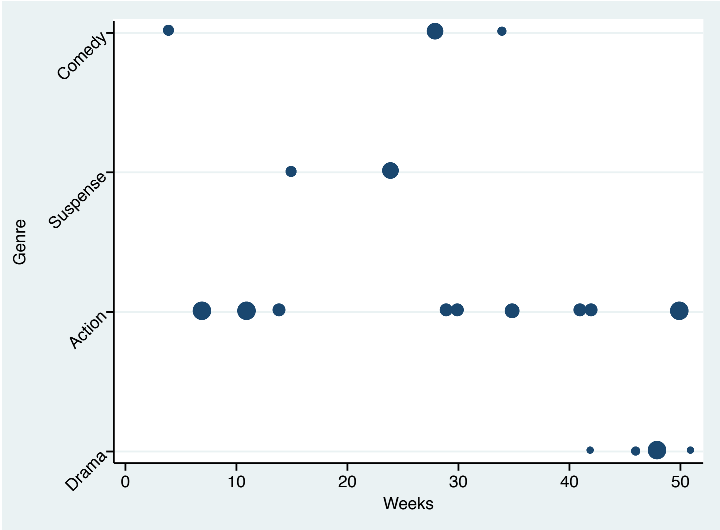

Figure 6: Movie releases by Fox in the U.S. in 2008

for a wider configuration of parameters under a multi-movie monopoly than under a duopoly. Moreover, when the monopoly studio decides to release both movies at date $t = 1$, we show that it chooses a lower budget than independent studios do (i.e., $a_i = (1-\beta)v_1/\gamma$ instead of $a_i = v_1/\gamma$). In contrast, when the monopoly studio opts for staggered releases, the chosen dates and budgets are exactly the same as in the duopoly case. The previous analysis suggests that the difference between coordinated (i.e., multi-movie monopoly) and independent (i.e., duopoly) decisions should only be minor and observed for a restricted set of parameters. Moreover, if we transpose these results to an oligopoly setting, i.e., if we add to our setting the competition resulting from other (multi-movie) studios, the impact of coordinated decisions can only be weaker. We therefore believe that the fact that the same studio releases several movies during a given season does not affect our results in any significant way.

International differences. Our dataset spans 10 countries but focuses on the release of American movies only. As a result, in non U.S. markets, we miss the competition that (unobserved) popular local movies exert on (observed) American movies. As anecdotal evidence, it appeared that Chinese authorities delayed the release of *Skyfall* (a James Bond movie) by more than three months with respect to the original release date, because an earlier release could have overshadowed the release of two big-budget Chinese films.[48] To account for such local competition we should definitely extend our dataset. For now, the potential influence of local movies is picked up in our regressions by the country fixed effects. Countries also differ according to the distribution of peaks along the year (because holidays, weather conditions and/or patterns of movie consumption vary across countries). However, this does not affect our estimations as peaks are defined country per country, which takes care of local specificities.

[48] See `www.hollywoodreporter.com/news/skyfall-china-release-date-pushed-389769`, last consulted March 2015.

Note that all our specifications are based on the assumption that country effects are fixed through the whole analysis period. As this could be seen as a restrictive assumption, we also tried an alternative model with different effects per country and per year. Yet, we did not observe any significant difference in the estimated parameters.[49]

Definition of genres. The degree of substitutability across movies (measured by the parameter β) plays an important role in our theoretical model. We approach it in the empirical analysis by classifying movies into different genres. There are two potential weaknesses in this strategy. First, our classification may be a bit arbitrary as we have merged distinct Mojo genres to form categories of relatively equal sizes. Although we have merged genres that looked relatively similar, we are not sure that the degree of substitutability is always higher across than within our categories. Second, and perhaps more importantly, recent developments in the motion picture industry indicate that the boundaries between various genres may start to blur. In particular, genres that used to be rather immune to competition like animated films are increasingly facing the competition of other genres, for instance superhero films.[50] Finally, as suggested by Cartier and Liarte (2012), demand peaks may also differ across genres (for instance, the demand for animated movies is more likely to peak during the Festive Season, when more families with young children go to theaters). In future work, we plan to check if our results still hold if we run our estimations under different groupings of the Mojo genres, or if we estimate demand peaks per genre.

6 Concluding remarks

In this paper, we analyzed how producers of cultural goods can strategically increase their expenditures in the attractiveness of their good to scare off the competition so as to secure a release date close to a demand peak. To this end, we built a simple game-theoretic model where two producers compete along two dimensions: attractiveness and release date. We showed that two types of subgame-perfect equilibria can emerge: simultaneous release (both producers choose high attractiveness expenditures and release their good at the start of the period, which corresponds to the peak of demand) or staggered release (one producer chooses a high attractiveness expenditure and releases its good at the start of the period, while the other producer chooses a lower attractiveness expenditure and releases its good later). The latter equilibrium is more likely when goods are close substitutes (e.g., because they belong to the same genre). We also extended the model by introducing uncertainty about how investments affect future attractiveness, as well as the possibility to change initial release dates.

We then applied the model to the motion picture industry, using a dataset of 1564 American movies released in 10 countries from 2002 to 2013. This allowed us to verify the predictions that we could draw from the theoretical model, namely that (i) higher budgets explain release dates closer to a demand peak, (ii) release dates are more sensitive to the budgets of close competitors

[49]The estimation results of this model are omitted here for the sake of brevity.

[50]See, e.g., `http://tinyurl.com/mdmqpdt` (last consulted March 2015) where Jeffrey Katzenberg explains how Marvel is Dreamworks new competition.

than of distant competitors, (iii) the mean and standard deviation of the budget distribution are both higher in weeks closer to a demand peak, and (iv) the release of movies with larger budgets is less likely to be rescheduled.

Besides the extension already mentioned in the previous section, it would be interesting in future research to test the predictions of our theoretical model for other cultural goods (e.g., books or video games).

7 Appendix

7.1 Justification of $\beta_0 > 1/2$

On average, it is reported that 40% of box-office revenues are secured during the the first week of exploitation of a movie. In our setting, this observation translates into

$$\int_1^2 \tau^{-\alpha} d\tau = \tfrac{4}{10} \int_1^{1+s} \tau^{-\alpha} d\tau \Leftrightarrow 1 + s = \left(\tfrac{10}{4} \left(2^{1-\alpha} - \tfrac{6}{10} \right) \right)^{\frac{1}{1-\alpha}} .$$

It is also reported that a movie is exploited during 6 to 8 weeks on average. Let us thus solve the above equation for $s \in \{6, 7, 8\}$. This will give us a value of α that we can then use, with the corresponding value of s, to compute β_0. The results of these computations are reported in the following table, where it is observed that the value of β_0 is significantly larger than 1/2 in all three instances. That allows us to conclude that the observation of 40% of revenues during the first week safely allows us to reject values of β_0 lower than 1/2.

s	$\alpha(s)$	β_0
6	1.193	0.753
7	1.281	0.796
8	1.344	0.826

7.2 Proof of Proposition 1

Step 1. Producer i's best response to $t_j \geq 1$ is either $t_i^* (t_j) = 1$ or $t_i^* (t_j) = t_j + s$.

We first show that the best conduct for a producer is to release its good either immediately or just after the other producer's good ceases to be sold. This result follows from the fact that segments R_a, R_b, and R_d decrease with t_i, while segment R_c reaches its largest value at one of the extremities of the zone where it is defined (i.e., at either $t_i = t_j$ or $t_i = t_j + s$). Formally,

$$R'_a = R'_d = (1 + a_i) \left(-t_i^{-\alpha} + (t_i + s)^{-\alpha} \right) < 0,$$

$$R'_b = -(1 + a_i) t_i^{-\alpha} + (1 + a_i - \beta a_j) (t_i + s)^{-\alpha} < 0.$$

As for segment R_c, we compute:

$$\begin{aligned} R'_c &= -(1 + a_i - \beta a_j) t_i^{-\alpha} + (1 + a_i) (t_i + s)^{-\alpha} , \\ R''_c &= \alpha \left((1 + a_i - \beta a_j) t_i^{-\alpha-1} - (1 + a_i) (t_i + s)^{-\alpha-1} \right) . \end{aligned}$$

If $R_c' = 0$, then $(1 + a_i - \beta a_j) = (1 + a_i)(t_i + s)^{-\alpha} t_i^{\alpha}$. Hence, $R_c'' = \alpha s (1 + a_i)(t_i + s)^{-\alpha-1} / t_i > 0$. So, either R_c decreases or increases with t_i on the whole range $t_i \in [t_j, t_j + s]$, or it has an interior minimum. That is, the largest value of R_c is reached either at $t_i = t_j$ or at $t_i = t_j + s$. In the former case, the whole profit function reaches its maximum at $t_i = 1$; in the latter case, it reaches its maximum at either at $t_i = 1$ or at $t_i = t_j + s$.

Step 2. If $t_j \geq 1 + s$, then producer i's best response is $t_i^* (t_j) = 1$.

This result is very intuitive: if the other producer releases its good after date $t = 1 + s$, it is possible to avoid upfront competition for the full life cycle by releasing one's good sufficiently earlier than the other producer does; moreover, as interest decays with time, it is optimal to release the good as soon as possible, i.e., at date $t = 1$. Formally, from Step 1, we know that $t_i^* (t_j) = 1$ or $t_i^* (t_j) = t_j + s$. As $t_j \geq 1 + s$, the former option brings producer i in profit segment R_a. To establish the result, we thus need to show that $R_a (1, t_j) > R_c (t_j + s, t_j)$. Developing the latter inequality, we have

$$\begin{cases} \frac{1}{1-\alpha}\left((1+s)^{1-\alpha} - 1\right) > \frac{1}{1-\alpha}\left((t_j + 2s)^{1-\alpha} - (t_j + s)^{1-\alpha}\right) & \text{for } \alpha \neq 1, \\ \ln(1+s) > \ln(t_j + 2s) - \ln(t_j + s) & \text{for } \alpha = 1. \end{cases}.$$

Let $x \equiv t_j + s$, $f(x) \equiv \frac{1}{1-\alpha}\left((x+s)^{1-\alpha} - x^{1-\alpha}\right)$, and $g(x) \equiv \ln(x+s) - \ln x$. We compute that $f'(x) = (x+s)^{-\alpha} - x^{-\alpha} < 0$ and $g'(x) = -s/(x(s+x)) < 0$, which implies that the above inequality is correct and completes the proof.

Step 3. Producer i's best response is to choose $t_i = 1$ if and only if $(1 + a_i)\beta_0 \geq \beta a_j$.

Three possible equilibria remain: simultaneous release ($t_1^* = t_2^* = 1$) and staggered release ($t_1^* = 1$ and $t_2^* = 1 + s$, or $t_1^* = 1 + s$ and $t_2^* = 1$). Suppose that $t_j = 1$. Then producer i's best response is to choose $t_i = 1$ if and only if $R_b(1,1) \geq R_c(1+s, 1)$, or

$$\begin{aligned} \int_1^{1+s} (1 + a_i - \beta a_j)\tau^{-\alpha} d\tau &\geq \int_{1+s}^{1+2s} (1 + a_i)\tau^{-\alpha} d\tau \Leftrightarrow \\ (1 + a_i - \beta a_j) v_1 &\geq (1 + a_i) v_s \Leftrightarrow \\ (1 + a_i)\beta_0 &\geq \beta a_j. \end{aligned}$$

The rest of the proposition directly follows.

7.3 Proof of Lemma 1

We compute:

$$\pi_1^{im} - \pi_1^d = \frac{\gamma}{2\beta^2}\left(-\underbrace{\left(\beta^2(2\beta - 1) + \beta_0(2\beta - \beta_0)\right)}_{+}\frac{v_1^2}{\gamma^2} - 2\beta_0\underbrace{(\beta - \beta_0)}_{+}\frac{v_1}{\gamma} + \beta_0^2\right)$$

So, $\pi_1^{im} \geq \pi_1^d$ if the polynomial in v_1/γ in the bracket is positive. Given the signs of the different terms and given that

$$(\beta_0(\beta - \beta_0))^2 + \left(\beta^2(2\beta - 1) + \beta_0(2\beta - \beta_0)\right)\beta_0^2 = 2\beta^3\beta_0^2,$$

we have that the polynomial is positive if

$$\frac{v_1}{\gamma} \leq \frac{\beta_0 (\beta - \beta_0) - \sqrt{2\beta^3 \beta_0^2}}{-\left(\beta^2 (2\beta - 1) + \beta_0 (2\beta - \beta_0)\right)} = \beta_0 \frac{\beta\sqrt{2\beta} - (\beta - \beta_0)}{\beta^2 (2\beta - 1) + \beta_0 (2\beta - \beta_0)},$$

which completes the proof.

7.4 Proof of Lemma 2

We first show that if condition (3) is met, then producer 1's best response to $a_2 = v_s/\gamma$ is $a_1 = v_1/\gamma$. We already know that $a_1 = v_1/\gamma$ is a best response locally (i.e., as long as $(1, 1+s)$ remains the ensuing equilibrium). Clearly, producer 1 cannot increase its profit by forcing the second-stage equilibrium to become $(1+s, 1)$. The only meaningful deviation is to reduce a_1 so that the second-stage equilibrium becomes $(1, 1)$. In that case, producer 1's problem is

$$\max_{a_1} \left(1 + a_1 - \beta\frac{v_s}{\gamma}\right) v_1 - \frac{\gamma}{2} a_1^2 \text{ s.t. } a_1 \leq \frac{\beta_0}{\beta}\left(1 + \frac{v_s}{\gamma}\right).$$

The optimum is $a_1 = v_1/\gamma$. Although we know that this value does not meet the constraint, let us suppose that it does for the sake of the demonstration. In this hypothetical case, producer 1's achieves the largest possible deviation profit, given by

$$\pi_1^d = \left(1 + \frac{v_1}{\gamma} - \beta\frac{v_s}{\gamma}\right) v_1 - \frac{\gamma}{2}\left(\frac{v_1}{\gamma}\right)^2.$$

Clearly, the deviation is not profitable even in this best-case scenario. We compute indeed that

$$\pi_1^{st} - \pi_1^d = \beta v_1 \frac{v_s}{\gamma} > 0.$$

Consider now producer 2. As indicated in the text, a first condition for $(a_1, a_2) = (v_1/\gamma, v_s/\gamma)$ to lead to second-stage equilibrium release dates $(t_1, t_2) = (1, 1+s)$ is condition (3), which can be rewritten as (by using $v_s = (1 - \beta_0) v_i$ and solving)

$$\frac{v_1}{\gamma} \geq \frac{\beta_0}{\beta}\left(1 + \frac{v_s}{\gamma}\right) \Leftrightarrow \frac{v_1}{\gamma} \geq \frac{\beta_0}{\beta_0^2 + \beta - \beta_0} \tag{8}$$

As shown on Figure 1, a condition for the deviation to $(1, 1+s)$ to be feasible is $\beta_0/\beta < (\beta - \beta_0)/\beta$, which is equivalent to $\beta > \frac{1}{2}(1+\sqrt{5})\beta_0 \simeq 0.618\beta_0$. We therefore distinguish between two cases.

(A) If $\beta_0 < \beta \leq \frac{1}{2}(1+\sqrt{5})\beta_0$, the only possible deviation for producer 2 is to change the second-stage equilibrium to $(1, 1)$. The necessary condition for such deviation is $(1 + a_2)\beta_0 \geq \beta\frac{v_1}{\gamma}$, or $a_2 \geq \frac{\beta}{\beta_0}\frac{v_1}{\gamma} - 1$. If the ensuing equilibrium is $(1, 1)$, producer 2 would optimally choose $a_2 = v_1/\gamma$. This value meets the latter condition if and only if $\frac{v_1}{\gamma} \geq \frac{\beta}{\beta_0}\frac{v_1}{\gamma} - 1$ or $\frac{v_1}{\gamma} \leq \frac{\beta_0}{\beta - \beta_0}$, which is compatible with condition (8). In that case, producer 2's profit is

$$\pi_2^d = \left(1 + (1 - \beta)\frac{v_1}{\gamma}\right) v_1 - \frac{\gamma}{2}\left(\frac{v_1}{\gamma}\right)^2.$$

We compute then

$$\pi_2^{st} - \pi_2^d = \frac{1}{2} v_1 \left(\left(\beta_0^2 + 2\left(\beta - \beta_0\right)\right) \frac{v_1}{\gamma} - 2\beta_0 \right).$$

Hence, the deviation is not profitable if $\pi_2^{st} \geq \pi_2^d$ or

$$\frac{v_1}{\gamma} \geq \frac{2\beta_0}{\beta_0^2 + 2\left(\beta - \beta_0\right)}. \tag{9}$$

where we check that the latter fraction is smaller than $\frac{\beta_0}{\beta - \beta_0}$ and larger than the RHS in (8). It is thus a necessary condition for a subgame-perfect equilibrium with staggered release.

Suppose now that $\frac{v_1}{\gamma} > \frac{\beta_0}{\beta - \beta_0}$. Producer 2 is constrained; the best it can choose is $a_2^d = \frac{\beta}{\beta_0} \frac{v_1}{\gamma} - 1$. The deviation profit becomes

$$\pi_2^{db} = \left(1 + \left(\frac{\beta}{\beta_0} \frac{v_1}{\gamma} - 1 \right) - \beta \frac{v_1}{\gamma} \right) v_1 - \frac{\gamma}{2} \left(\frac{\beta}{\beta_0} \frac{v_1}{\gamma} - 1 \right)^2$$

We compute

$$\pi_2^{st} - \pi_2^{db} = \frac{1}{2} \frac{\left(-\gamma\beta_0 + \beta v_1 - \beta_0 v_1 + \beta_0^2 v_1\right)^2}{\gamma \beta_0^2} > 0,$$

which shows that the deviation is not profitable in this case.

(B) Consider now the case where $\frac{1}{2}(1+\sqrt{5})\beta_0 \leq \beta \leq 2\beta_0$. Condition (9) remains necessary to make sure that producer 2 does not deviate so as to change the second-stage equilibrium to $(1,1)$. Compared to the previous case, there is now an additional possibility of deviation, which consists in changing the second-stage equilibrium to $(1+s,1)$. For this deviation to be feasible, it must be the case (see Figure 1) that $v_1/\gamma < \left(\beta - \beta_0\right)/\beta_0$. But, we have just argued that condition (9) remains necessary. We now show that if (9) is satisfied, then $v_1/\gamma > \left(\beta - \beta_0\right)/\beta_0$, making the deviation to $(1+s,1)$ impossible. Suppose not. Then

$$\frac{\beta - \beta_0}{\beta_0} > \frac{2\beta_0}{\beta_0^2 + 2\left(\beta - \beta_0\right)},$$

which implies that

$$\beta > \frac{1}{4}\left(4 - \beta_0 + \beta_0\sqrt{\beta_0^2 + 16}\right) \equiv \hat{\beta}.$$

But that leads to a contradiction as $\hat{\beta} > 1$ for all admissible β_0 and $\beta \leq 1$ by definition.

We therefore conclude that only the deviation to $(1,1)$ is feasible and it is not profitable if condition (9) holds, which completes the proof.

7.5 Multiproduct monopoly

To be able to compare the monopoly and duopoly situations, we continue to assume an exogenous degree of substitutability between the two goods (i.e., β).[51] Clearly, the monopolist chooses to release at least one good at date $t = 1$ (there is indeed nothing to be gained by delaying the release of the two goods). By the same token, the producer will release the second good no later

[51] Arguably, a monopoly producer is also able to choose the degree of good differentiation, insofar as it can avoid to release goods of the same genre during the same period.

than date $t = 1 + s$. The monopolist's problem is thus to choose a_1, a_2 and t_2 so as to maximize its total profits on the two goods:

$$\begin{aligned}
\Pi^m &= \int_1^{t_2} (1 + a_1)\,\tau^{-\alpha} d\tau + \int_{t_2}^{1+s} (2 + (1-\beta)(a_1 + a_2))\,\tau^{-\alpha} d\tau \\
&\quad + \int_{1+s}^{t_2+s} (1 + a_2)\,\tau^{-\alpha} d\tau - \frac{\gamma}{2}\left(a_1^2 + a_2^2\right), \\
\text{s.t. } 0 &\leq a_1, a_2 \leq 1 \text{ and } 1 \leq t_2 \leq 1 + s.
\end{aligned}$$

Deriving profit with respect to a_1 and a_2 gives

$$\begin{aligned}
\frac{\partial \Pi^m}{\partial a_1} &= \int_1^{t_2} \tau^{-\alpha} d\tau + (1-\beta)\int_{t_2}^{1+s} \tau^{-\alpha} d\tau - \gamma a_1 = 0 \\
&\Leftrightarrow\ a_1^*(t_2) = \tfrac{1}{\gamma}\left(\tfrac{t_2^{1-\alpha}-1}{1-\alpha} + (1-\beta)\tfrac{(1+s)^{1-\alpha}-t_2^{1-\alpha}}{1-\alpha}\right) \\
\frac{\partial \Pi^m}{\partial a_2} &= (1-\beta)\int_{t_2}^{1+s} \tau^{-\alpha} d\tau + \int_{1+s}^{t_2+s} \tau^{-\alpha} d\tau - \gamma a_2 = 0 \\
&\Leftrightarrow\ a_2^*(t_2) = \tfrac{1}{\gamma}\left(\tfrac{(t_2+s)^{1-\alpha}-(1+s)^{1-\alpha}}{1-\alpha} + (1-\beta)\tfrac{(1+s)^{1-\alpha}-t_2^{1-\alpha}}{1-\alpha}\right)
\end{aligned}$$

Deriving profit with respect to t_2 gives

$$\begin{aligned}
\frac{\partial \Pi^m}{\partial t_2} &= (1 + a_1)\,t_2^{-\alpha} + (1 + a_2)(t_2 + s)^{-\alpha} - (2 + (1-\beta)(a_1 + a_2))\,t_2^{-\alpha} \\
&= \beta (a_1 + a_2)\,t_2^{-\alpha} - (1 + a_2)\left(t_2^{-\alpha} - (t_2 + s)^{-\alpha}\right).
\end{aligned}$$

Substituting $a_1^*(t_2)$ and $a_2^*(t_2)$ for a_1 and a_2, we have an expression that depends only on t_2 and on the parameters. Deriving again with respect to t_2, we can try to establish the sign of $\partial^2\Pi^m/\partial t_2^2$. Unfortunately, we have not found any simple analytical way to do so. However, a large number of numerical simulations consistently show that $\partial^2\Pi^m/\partial t_2^2 > 0$, suggesting that the producer's profit is convex in t_2. If so, the optimal release date for the second good is either $t_2 = 1$ or $t_2 = 1+s$. Let us compare the two options. If $t_2 = 1$, then $a_1^*(1) = a_2^*(1) = \frac{1}{\gamma}(1-\beta)\,v_1$ and $\Pi^m(1) = (v_1/\gamma)\left(2\gamma + v_1(1-\beta)^2\right)$. If $t_2 = 1 + s$, then $a_1^*(1+s) = \frac{1}{\gamma}v_1$, $a_2^*(1+s) = \frac{1}{\gamma}v_s$ and $\Pi^m(1+s) = (1/2\gamma)\left(v_1^2 + v_s^2 + 2\gamma(v_1 + v_s)\right)$. Then, the optimum is $t_2 = 1$ if and only if $\Pi^m(1) \geq \Pi^m(1+s)$, which is equivalent to

$$\frac{v_1}{\gamma} \leq \frac{2\beta_0}{2\beta(1-\beta) + 2(\beta - \beta_0) + \beta_0^2}.$$

It can be shown that the RHS of the latter condition is larger than the RHS in Condition (2), meaning that *simultaneous release emerges for a wider configuration of parameters under a multi-good monopoly than under a duopoly.*

7.6 Additional tables and figures

	Winter (1-8)	Spring (9-17)	Summer (18-34)	Fall (35-42)	Holiday (43-52)
Australia	1/2	15/16	26/27/28	39/40	52
France	7/8	9	28/29	42	51/52
Germany	1/2 - 5/6/7	9	20/21 - 29/30	40	51/52
Italy	1/2/3	10/11	20	37 - 42	51/52
Japan	4	16	18 - 28/29/30/31/32/33	37	50/51
New Zealand	1/2	16	26/27/28/29	40	47 - 52
South Africa	1	12/13/14/15	26/27/28/29	39/40	48/49/50/51
Spain	1 - 6/7	10	32	41	47/48/49 - 51/52
US / Canada	7	14	21 - 26/27/28	35	51/52
UK	1 - 7	14	21 - 28/29/30	42	43/44 - 46/47

Table 4: Weeks qualifying as peaks (seasonal basis)

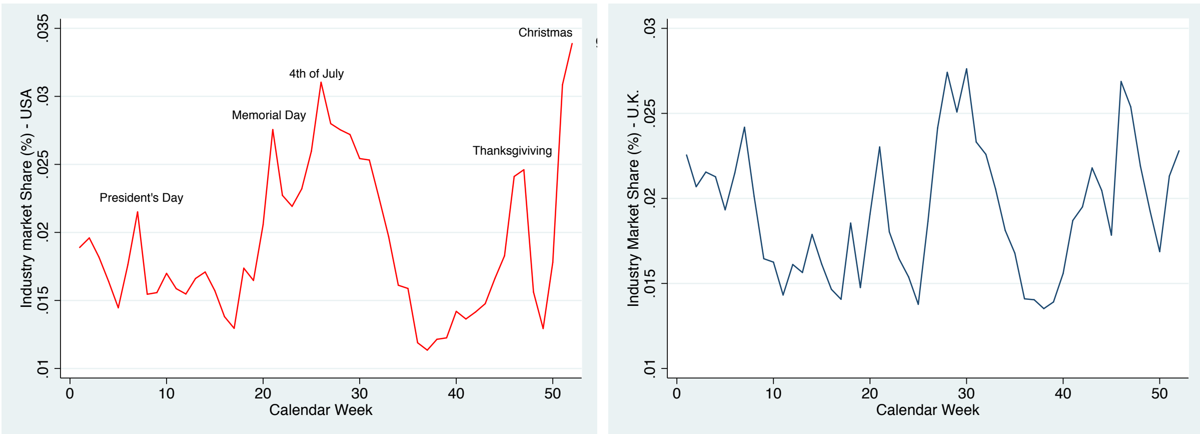

Figure 7: Estimated seasonal peaks (left: US/Canada (left); right: UK)

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	Winter (1-8)	Spring (9-17)	Summer (18-34)	Fall (35-42)	Holiday (43-52)
Australia	1/2/3/4		23 - 26/27/28/29	40	52
	1/2	15/16	26/27/28	39/40	52
France	5/6/7/8/9				43/44 - 48/49 -51/52
	7/8	9	28/29	42	51/52
Germany	1		20/21 - 29/30/31	40	46/47 - 51/52
	1/2 - 5/6/7	9	20/21 - 29/30	40	51/52
Italy	1/2/3/4/5	10			44 - 47/48 - 51/52
	1/2/3	10/11	20	37 - 42	51/52
Japan		16	18 - 27/28/29/30/31/32/33		50/51
	4	16	18 - 28/29/30/31/32/33	37	50/51
New Zealand	1/2	16	21 - 25/26/27/28/29/30		52
	1/2	16	26/27/28/29	40	47 - 52
South Africa	1	14	18 - 26/27/28/29/30	39	48 - 51
	1	12/13/14/15	26/27/28/29	39/40	48/49/50/51
Spain	1 - 4/5/6/7			41	47/48/49 - 51/52
	1 - 6/7	10	32	41	47/48/49 - 51/52
US / Canada			21 - 25/26/27/28/29/30/31		47 - 51/52
	7	14	21 - 26/27/28	35	51/52
UK	7		21 - 27/28/29/30/31/32		46/47
	1 - 7	14	21 - 28/29/30	42	43/44 - 46/47

For each country, the first (second) line indicates the weeks qualified as peaks on a yearly (season) basis

Table 5: Weeks qualifying as peaks (yearly basis)

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