

Movie Release Strategy: Theory and Evidence from International Distribution

Luís Cabral
New York University

Gabriel Natividad
Universidad de Piura

May 2019

Abstract. Choosing the right time to release a new movie may be the difference between success and failure. Prior research states that the “bigger” a blockbuster is, the more likely it is (and should be) released during a high-demand week. We present a theoretical framework which is consistent with this observation but adds a rather surprising theoretical prediction: among non-blockbuster movies, everything else constant, the greater a movie’s appeal, the more likely it is released during a low-demand week. We provide intuition for this novel result and argue that it is robust to a number of changes in functional form assumptions. We then show that the theoretical results are consistent with the evidence from an extensive dataset on international releases. Specifically, we run a series of movie-country-pair regressions with high-demand-week-release as a dependent variable and exogenous shocks to the movie’s appeal as an explanatory variable. As predicted by theory, the regression coefficients have opposite signs for the blockbuster and non-blockbuster cases.

Cabral: Stern School of Business, New York University; luis.cabral@nyu.edu. Natividad: Universidad de Piura; gabriel.natividad@udep.pe. We are grateful to audiences at Pontificia Universidad Catolica de Chile, Universidad de Piura, the 2017 Mallen conference on the Economics of Filmed Entertainment, the 2018 Munich Summer Institute, and to Justin Tumlinson (discussant) for comments on previous drafts. We are grateful to Cristián Figueroa, Walter Noel, Leandro Pezán, Juan Ferrer, and Mariagracia Gálvez for valuable research assistance. Last but not least, we thank the co-editor and especially a referee for extensive comments and suggestions which had a substantial impact on the paper’s revision process. We alone remain responsible for any remaining errors and deficiencies.

1. Introduction

As shown by Cabral and Natividad (2016) and others, a movie’s performance during opening weekend is an important determinant of its eventual overall success. More generally, the choice of a release date is one of the most important strategic decisions a distributor has to make (advertising being another one). There are several trade-offs to take into account when it comes to picking an opening weekend. On the one hand, choosing a high-demand weekend allows the distributor to tap into a larger potential demand. On the other hand, it’s more likely than not that several other distributors open during a high-demand weekend, which implies fiercer competition. Industry players recognize the importance of this strategic dimension and how it can turn into a “highly destructive game.”

In this paper, we characterize the demand-competition trade-off in the choice of a release date. We develop a game-theoretic framework which contemplates two possible extreme cases: If the competing movies are sufficiently large (blockbusters) — so that a particular movie’s release decision has a measurable impact on rival movies’ demand — then, in equilibrium, the greater a movie’s appeal, the more likely the movie is released during a high-demand week. In the limit, if a blockbuster is the single super-mega-blockbuster of the year, then it takes over whatever weekend it opens; and it thus optimally opens during the highest-demand weekend. This is not entirely surprising and is in line with prior theoretical and empirical evidence (Krider and Weinberg, 1998; Einav, 2007).

Perhaps more surprisingly, we also show that, if the competing movies are sufficiently small (niche movies) — so that a particular movie’s release decision has no measurable impact on rival movies’ demand — then, in equilibrium, the greater a movie’s appeal, the more likely the movie is released during a *low*-demand week. To understand the intuition for this result, note that, in this measure-zero-movie extreme world, a movie’s decision is one of individual optimization against the field. Since in equilibrium many more movies flock to the high-demand period, the marginal return to movie-specific appeal, which is related to the ratio between a movie’s appeal and the aggregate appeal of rival releases during a given period, is *smaller* during the high-demand period. This in turn implies that the trade-off between period-specific demand and period-specific competition leads higher-appeal niche movies to prefer lower-demand periods.

Our theoretical results are based on specific assumptions regarding movie demand and on extreme cases regarding movie appeal (mega-blockbuster or measure-zero niche). In order to test the robustness of these predictions, we consider a series of simulations with more general distributions of movie appeal and different demand functional forms. These simulations confirm the change in sign of a movie’s release strategy as we move from niche to blockbuster movies.

We then test the theory’s predictions on data from international movie releases (14,773 distinct feature films from 87 production countries distributed in 56 destination countries). This data has two advantages. First, given that we have a matrix of country of origin and country of release, we have a large number of observations of demand and release date for each of our movies. Second, by measuring exogenous shocks to the proximity of two countries, we are able to measure variations in a movie’s appeal, thus avoiding the common problem of unobserved characteristics in supply and demand estimation.

Specifically, following Voeten et al. (2017) and Signorino and Ritter (1999), we use United Nations voting behavior as a measure of political affinity between each country pair.

Our identification strategy is based on the assumption that variations in political affinity between countries i and j have an effect on the appeal of movies produced in country i when shown in country j . Naturally, there are many different factors which influence movie demand aside from political affinity. All that our estimation strategy requires is that an increase in political affinity leads to greater appeal. For example, Chile and Venezuela can be said to be culturally close on a variety of dimensions, including language. In the current state of affairs, the two countries cannot be said to be politically close. Our point is that, were Venezuela to change its political regime to one that is closer to Chile, we would say the two countries become even closer; this increase in political affinity would be measured (with noise) by the two countries' United Nations voting behavior; and ultimately, we would expect an increase in demand for Venezuelan movies in Chile and Chilean movies in Venezuela (everything else constant).

Our empirical estimates confirm the theoretical model's predictions. In order to split our sample into blockbusters and niche movies — and then test for the change in release strategy by type of movie — we consider various measures of potential movie appeal: budget, star cast, and number of release screens.¹ We then consider blockbusters to be movies with high value of each of these potential appeal variables. Specifically, for each of these measures we split our sample into the top quintile and the bottom four quintiles.² As expected, the data shows a positive relation between shifts in movie appeal, measured by shifts in political affinity, and propensity to release during high-demand weeks for blockbusters (top quintile) and a negative one for niche movies (bottom quintiles). The results are robust in a variety of ways, including different ways of splitting the sample.

■ **Related literature.** Our paper relates to an economics, marketing and strategy literature dealing with the business of motion pictures, namely the choice of a movie release date (Krider and Weinberg, 1998; Einav, 2007; Chiou, 2008). These papers focus on blockbuster movies. By contrast, we focus both on blockbusters and on lower-appeal movies as well. In fact, our main theoretical contribution is to show that an optimal release strategy depends greatly on the nature of the movie (in terms of its appeal).

A related economics, marketing and strategy deals with the international performance of motion pictures (Neelamegham and Chintagunta, 1999; Elberse and Eliashberg, 2003; Craig et al., 2005; Kim and Jensen, 2014). However, the focus of these papers is on the relation between country proximity and movie performance. Similarly to these papers, we test our theory on a dataset of international movie releases, and we do use a measure of country proximity. However, we do this in order to test theoretical results regarding optimal release strategies.

Finally, we are not the first to use UN voting data as a measure of country proximity (Stone, 2004; Simmons, 2005; Bertrand et al., 2016). However, these papers deal with different issues, typically related to trade and finance, rather than the economics of movie distribution.

■ **Roadmap.** The rest of the paper is organized as follows. In Section 2 we propose a simple model of movie demand and supply which provides fairly sharp predictions regarding the

1. These are obviously noisy measures, but typically a blockbuster is a high-budget movie with strong star power and it opens in a large number of screens.

2. We implemented various possible splits. We discuss this further in Section 4.

relation between movie appeal and the optimal movie-release strategy. Section 3 presents a series of simulations which serve as a robustness check on various aspects of the theoretical analysis. Section 4 tests the theoretical results on data from international releases. Finally, Section 6 concludes the paper.

2. Theory

This section is divided in two separate parts. First, we assume that movies are sufficiently small that their individual release strategy does not affect other movies' payoff. We refer to this as the niche-movie case. We then consider the opposite extreme case, namely the case when there are only two movies, each of which is sufficiently large that a particular movie's release strategy has a significant effect on the rival movie's payoff. We refer to this as the blockbuster case.

Suppose first that there is a measure n of movies, which we will also refer to as the number of movies. We assume price and advertising expenditures are fixed, so that the sole strategy by distributors is to decide when to release the movie. As shown by Einav (2007), there are a few select weekends throughout the year when demand is particularly high. To capture this variation, we assume that there are two possible release periods: $t = 1, 2$. With no loss of generality, we assume that $t = 2$ corresponds to a high-demand period. Specifically, demand for movie i when released in period t is given by

$$d_{it} = (\alpha + q_i/Q_t) \beta_t \quad (1)$$

where q_i is a movie- i -specific demand parameter and Q_t is the total supply of movies (in the same units) in period t ,

$$Q_t = \int_{k \in S_t} q_k dk, \quad (2)$$

where S_t is the set of all movies released in period t .³ Throughout the paper, we refer to q_i as “movie appeal”. For the purpose of our theory, we treat it as a scalar. In reality, a movie's appeal is likely to result from many different factors. In fact, in our empirical section we will consider several ones.

The idea underlying the above demand system is that, in a given period, a movie's demand consists of a fixed component and a variable component. The fixed component corresponds to moviegoers who will watch the movie regardless of what its competition is. The variable component, by contrast, corresponds to moviegoers with a fixed “budget” (in terms of time or money or both). This implies that, the more movies are released in a given period, the lower the demand faced by a given movie. Finally, demand variations across periods are parameterized by a multiplier β_t , where, consistently with our assumption that $t = 2$ is a “hot” period, we make the following assumption:

3. As the proof of Proposition 1 below shows, the result is not knife-edged with respect to the assumption that the value of α is the same in both periods. In other words, if the difference between α_1 and α_2 is small with respect to the difference between β_1 and β_2 then the result carries through. We believe our demand structure makes empirical sense. It also allows us to derive sharp theoretical results. That said, we acknowledge that it is not entirely standard from an empirical demand estimation perspective. For this reason, in the next section we consider alternative functional forms, as well, and show that the same qualitative results apply.

Assumption 1. $\beta_2 > \beta_1$

An equilibrium consists of a set of release strategies $T(q_i)$, where $T(q_i) \in \{1, 2\}$, such that for every film i demand from releasing at $T(q_i)$ is greater than demand from releasing during the alternative release date. Our first result provides a sharp prediction regarding the relation between the movie-specific demand parameter q_i and movie release strategy.

Proposition 1. *There exists a threshold q' such that, in equilibrium, a movie is released at $t = 2$ if and only if $q_i < q'$.*

Proof: Let q' be the demand index of a movie distributor which is indifferent between $t = 1$ and $t = 2$:

$$(\alpha + q'/Q_1) \beta_1 = (\alpha + q'/Q_2) \beta_2$$

Since $\alpha \beta_2 > \alpha \beta_1$, it follows that $\beta_1/Q_1 > \beta_2/Q_2$. Therefore,

$$\frac{\partial d_1}{\partial q'} = \beta_1/Q_1 > \beta_2/Q_2 = \frac{\partial d_2}{\partial q'}$$

This implies that all movies with $q > q'$ (resp. $q < q'$) strictly prefer to release at $t = 1$ (resp. $t = 2$). ■

Intuitively, a period of greater demand attracts more movie openings (Einav, 2007). This means that the relative value of a movie with greater specific demand is lower during a high-demand period: it has to compete against more movies. To put it differently, “autonomous” demand $\alpha \beta_t$ is greater at $t = 2$. Since this demand component is independent of movie-specific demand q , the high-demand period attracts relatively lower q movies. In relative terms, the autonomous component of demand is worth more for these movies.

Proposition 1 formally establishes that high demand during a given period and high movie-specific demand are substitute factors: the greater the level of general demand in a given period, the lower the marginal effect of an increase in movie-specific demand.

In a similar but different setup, Krider and Weinberg (1998) provide the opposite prediction. Their movie-release game considers the simultaneous choice by two movies with different levels of attraction. Although there may exist multiple equilibria to their game, their results suggest that, when the two players and the two periods are sufficiently asymmetric, the more appealing movie tends to open during the high-season, whereas the weak movie prefers to avoid head-to-head competition.

To see this, we consider a simplified version of the game they consider which can be cast in terms similar to our release-date game. As before, suppose there are two periods, $t = 1, 2$. Differently from before, suppose that there are only two movies, a and b . The movie demand function is as before, with the difference that we now do not treat movies as a finite number rather than as a continuum.

Specifically, similarly to the continuum case, demand for movie i when released in period t is given by (1). As to Q_t , the total supply of movies in period t , instead of (2), we now have $Q_t = q_i$ if only movie i is released and $Q_t = q_a + q_b$ if both movies are released. We maintain Assumption 1 and add a second assumption:

Assumption 2. $\beta_2 < \frac{1+\alpha}{\alpha} \beta_1$

Figure 1

Blockbuster release-date game

		Movie b	
		t_1	t_2
Movie a	t_1	$\left(\alpha + \frac{q_b}{q_a + q_b}\right) \beta_1$	$(\alpha + 1) \beta_2$
	t_2	$(\alpha + 1) \beta_1$	$\left(\alpha + \frac{q_b}{q_a + q_b}\right) \beta_2$

Note that Assumptions 1 and 2 define a non-empty set of parameter values. Basically, we require that β_2 be greater than β_1 (Assumption 1) but not much greater (Assumption 2).

Since we have two players and two strategies, the simultaneous-move game may be represented in matrix form, which we do in Figure 1. Normally, entry-type games such as this one admit multiple equilibria (two asymmetric pure-strategy equilibria and a mixed-strategy equilibrium). However, if players are sufficiently asymmetric, then a unique equilibrium ensues, as the next result establishes.

Proposition 2. *There exists a $\epsilon > 0$ such that, if $q_a/(q_a + q_b) < \epsilon$, then the release-date game admits a unique equilibrium: a at $t = 1$, b at $t = 2$.*

Proof: The conditions that $t = 2$ is a dominant strategy for b and $t = 1$ is a 's best response to $t = 2$ by b are, respectively,

$$\begin{aligned} \left(\alpha + \frac{q_b}{q_a + q_b}\right) \beta_2 &> (\alpha + 1) \beta_1 \\ \left(\alpha + \frac{q_a}{q_a + q_b}\right) \beta_2 &< (\alpha + 1) \beta_1 \end{aligned}$$

If $q_a/(q_a + q_b) = 0$, then this reduces to

$$\begin{aligned} (\alpha + 1) \beta_2 &> (\alpha + 1) \beta_1 \\ \alpha \beta_2 &< (\alpha + 1) \beta_1 \end{aligned}$$

which follow from Assumptions 1 and 2, respectively. Finally, the result follows by continuity. ■

Propositions 1 and 2 imply opposite predictions. Proposition 1 states that higher-demand movies are released during low-demand periods, whereas Proposition 2 states that higher-demand movies are released during high-demand periods. The crucial difference between the two results is that the first result is based on a continuum-player game, whereas the second result is based on a two-player game with very asymmetric players.

Consider first the two-player game with asymmetric players. In the limit, a blockbuster takes over whatever market it enters; that is, movie b 's market share is 100% regardless of the other movie's choice. Consequently, it is optimal (a dominant strategy) for the

blockbuster to enter during the high-demand period. This result corresponds to the model developed by Krider and Weinberg’s (1998) as well as the empirical evidence from US wide releases (Einav, 2007; Chiou, 2008).

At the opposite end, in the continuum case a movie’s choice of $t = 1$ or $t = 2$ does not affect the total supply during that period. The equilibrium is thus one of individual optimization against the field. Since many more movies flock to the high-demand period, the marginal return to movie-specific appeal, q/Q , is small during the high-demand period, which in turn explains why high-demand movies prefer the low-demand release period.

3. Numerical simulations

Our theoretical results are based on two limiting cases: niche movies are treated as measure-zero entities, and a top blockbuster is considered to be of infinite quality. In this section we consider a more realistic setting where niche products are small but not measure zero and blockbusters are large but not infinite. The goal is to assess whether the equivalent of Propositions 1 and 2 applies in this more realistic case. Specifically, the prediction is that, among niche products, an increase in movie-specific appeal leads to a lower propensity of release during the high-demand period, whereas, among blockbusters, an increase in movie-specific appeal leads to a higher propensity of release during the high-demand period.⁴

We generate a pseudo data set of movie appeal and movie release decisions by solving a series of entry games. In each game, we assume there are n players ($n = 20$ in our base case) divided into n_1 niche movies ($n_1 = 18$ in our base case) and n_2 blockbuster movies ($n_2 = 2$ in our base case). We assume the appeal of a niche movie is measured by a parameter q which is uniformly distributed in $[0, b_1]$ ($b_1 = 1$ in our base case), whereas a blockbuster’s appeal is measured by a parameter q which is uniformly distributed in $[0, b_2]$ ($b_2 = 100$ in our base case).

As before, demand for movie i if released at time t is given by

$$d_{it} = \left(\alpha + \frac{q_i}{\sum_{j \in S_t} q_j} \right) \beta_t \quad (3)$$

where S_t is the set of movies released during period t .

The movie release game is an entry game, and entry games are known for admitting multiple equilibria (Propositions 1 and 2 correspond to limit cases in which a unique equilibrium exists). We take care of the equilibrium selection problem by randomizing initial strategies and then iteratively solving for each player’s best response until convergence is reached.⁵

We solve the game in this way 100 times and thus generate 2,000 observations of movie appeal and movie release strategy ($t = 1$ or $t = 2$). We then run a regression where the dependent variable is the release strategy (1 if $t = 2$) and the independent variable is movie appeal. In order to distinguish the effects underlying Propositions 1 and 2, we interact the independent variable q_i with dummies for blockbuster (budget greater than 1 million) and niche (budget lower than 1 million).

4. In other words, the propensity to open during a high-demand week has a U-shaped relation with movie-specific appeal.

5. Although we are not aware of a result that guarantees convergence of this iterative process, in our simulations we always obtained convergence after a few iterations.

In our base case, we assume the parameters of the demand function (3) are given by $\alpha = .01$ and $\beta = 3$. The results of our release-strategy regressions can be found in Table 1. We consider two different estimation models, a linear probability model and a probit model. In both cases the estimated coefficients have the signs predicted by Propositions 1 and 2.

The niche-movie coefficient in the linear probability model, $-.92$, suggests that an increase in q from 0 to 1 causes an almost complete shift from releasing at time $t = 1$ (high demand) to $t = 0$ (low demand). In other words, if you have a particularly low-appeal niche movie you are better off releasing it during a period of high demand. The blockbuster-movie coefficient in the linear probability model, 0.002 , suggests that an increase in q from 0 to 100 causes an increase in the probability of releasing at time $t = 2$ (high demand) of about 20%. In other words, if you have a particularly large blockbuster movie you are better off releasing it during a period of high demand.

Such large shifts in probability suggest that the approximation provided by a linear probability model is not a good approximation. For this reason, we also estimate the relation between movie quality and release strategy using a probit model. Although the coefficient estimates are not as easy to interpret as in the linear probability model, we note that the coefficient estimates have the predicted sign and are estimated with statistical precision.

One possible criticism of our theoretical model is that it is based on a very specific demand functional form, in particular one that differs from standard functional forms used in the empirical literature (Einav, 2007; Chiou, 2008). For this reason, we repeat our numerical simulation with a more standard demand function: the logit demand function. Suppose that, each period, there are β_t potential moviegoers, and that each moviegoer chooses at most one movie to watch. Suppose that the moviegoer k 's utility of watching movie i is given by $q_i + \epsilon_{ik}$, whereas the outside option of not watching any movie is worth α . Assuming that ϵ_{it} follows a Weibull distribution, the demand for movie i if released at time t is given by

$$d_{it} = \left(\frac{\exp(q_i)}{\exp(\alpha) + \sum_{j \in S_t} \exp(q_j)} \right) \beta_t \quad (4)$$

where S_t is the set of movies released during period t (Train, 2009).

In our base case, we assume the parameters of the demand function (4) are given by $\alpha = 0$ and $\beta = 2$. The results of our release-strategy regressions with the logit demand system can be found in Table 2. As before, we consider two different estimation models, a linear probability model and a probit model. In both cases the estimated coefficients have the signs predicted by Propositions 1 and 2. However, the coefficient estimates have a lower level of statistical significance than in the linear-demand case.

To conclude this section, we should mention that the results of our numerical simulations are not knife-edged, that is, they are robust to small changes in the exogenous parameter values. However, different values of α and β result in different coefficient estimates, sometimes estimates that are not statistically significant, sometimes estimates that have the opposite sign of what's predicted by Propositions 1 and 2. That said, the exercise presented in this section serves to make two points. First, the somewhat surprising idea that higher-appeal moves may prefer to release during a lower-demand period is not outlandish. It makes sense from a theoretical point of view and it seems robust to the use of different functional forms for demand. Second, the relation between movie appeal and movie release

strategy depends crucially on the nature of the movie, namely whether it is closer to a niche movie (which competes against the field) or closer to a blockbuster movie (whose actions have a significant impact on other movies).

4. Empirical test

In this section we test our theory using actual movie release data. Specifically, we focus on international distribution: the release in country b of a movie produced in country a . International releases provide a particularly good setting for testing Propositions 1 and 2 for two reasons. First, a matrix of international demand values and release dates provides a large number of observations to work with. Second, and more important, international releases allow us to implement an identification strategy based on cultural proximity which addresses the always thorny endogeneity issue in regressions of the sort considered in Section 3 and below.

■ **Data and variables.** We assembled our database on movie characteristics from the Internet Movie Database (IMDb). IMDb includes information on the nationality of production companies, cast, and importantly release date in each country. The resulting data set includes 14,773 distinct feature films from 87 production countries distributed in 56 destination countries in the sample period of interest.

Of particular importance is the date at which movie i is released in country j . For each country and year, we define the top five weekends as those that had the highest gross revenues in the previous year.⁶ We also define as high-demand weekend the weekends following the above top five weekends.⁷ This allows us to create a binary variable, R_{ij} , which equals 1 if movie i was released in country j during a high-demand period, zero otherwise.

$$R_{ij} = \begin{cases} 1 & \text{if movie } i \text{ is released in country } j \text{ during high-demand week} \\ 0 & \text{otherwise} \end{cases} \quad (5)$$

Our theory implies specific predictions regarding the relation between a movie’s appeal, q_i , and the movie’s release strategy, $T(q_i)$. The difficult part in testing the theory is to obtain a good measure of q_i . Box-office performance measures suffer from endogeneity problems: A movie’s demand is a function of its appeal as well as the period when it’s released. Moreover, the release decision is likely influenced by information observed by the distributor but not by the econometrician.

Our identification strategy is based on an estimate of *variations* in q_i . Specifically, we assume that, everything else constant, the political affinity between countries i and j positively influences the appeal in country j of a movie produced in country i . Specifically, we measure each country pair’s political affinity based on their United Nations (UN) voting behavior.

6. Einav (2007) shows, with US data, that high supply meets high demand, that is, the weekends of highest demand are also the weekends when the biggest blockbusters are released. This suggests that, in equilibrium, the highest-grossing weekends are the ones with highest demand (that is, the supply effect reinforces the demand effect).

7. Our coding convention is robust to alternative definitions of top weekend.

The voting data is drawn from the Voeten et al. (2017) repository, publicly available online. This data set contains the roll call votes of all countries in the UN General Assembly over the sample period for the global film sales data set described above. The similarity variable S that proxies for the affinity between countries (Signorino and Ritter, 1999) is a statistic that describes the similarity between the voting patterns of two countries in the UN General Assembly. For each country i voting on resolution r , define $P_r^i = 1$ if the country votes “Yes”, $P_r^i = 0$ if it votes “Abstain” and $P_r^i = -1$ if it votes “No”. Thus, considering two countries i and j in year t , their bilateral affinity measure is defined as:

$$S_{ijt} = 1 - \frac{2 \sum_{r=1}^R |P_r^i - P_r^j|}{2R}, \quad (6)$$

where R is the total number of resolutions in year t . The measure S takes values between -1 and $+1$, with higher values of S reflecting more similar voting patterns between the two countries. By construction, $S_{iit}=1$, that is, the affinity between a country and itself, is always 1.

Finally, we define a *political affinity shocks* as the change in the political affinity variable S from year $t - 1$ to year t :

$$D_{ijt} \equiv S_{ijt} - S_{ij(t-1)} \quad (7)$$

where i denotes the producing country, j the country of exhibition, t the time period, and S_{ijt} is defined by (6). Whenever there is more than one movie production country, we average the political affinity shock between production countries and the release country.⁸

How well does this measure capture the affinity between two countries? The vast literature following Signorino and Ritter (1999) is arguably a testament to its usefulness, but one might ask whether this variable correlates well with other measures of bilateral affinity for our period of interest. Unfortunately, the only alternative time-varying proxy for bilateral trust employed in the literature was available in the Eurobarometer survey and ended in 1997, a few years before our start date. That variable recorded answers to a survey of citizens from various developed countries.⁹ When comparing this survey’s 1997 answers with the values of the S variable also for 1997 we find, reassuringly, a correlation coefficient of 0.14, with a p -value of 0.027. We thus see S as a reasonable proxy for bilateral affinity in light of other measurement approaches.

We readily admit that political preferences — in particular the way we measure them — correspond to a very small fraction of a given country’s makeup. Moreover, the proximity between two countries involves many dimensions — economic, cultural, etc. — that go beyond political affinity. For the purpose of our empirical exercise, the important identifying assumption is that political affinity contributes to proximity more broadly defined. For example, Chile and Venezuela can be said to be culturally close on a variety of dimensions, including language. In the current state of affairs, the two countries cannot be said to be politically close. Our point is that, were Venezuela to change its political regime to one that is closer to Chile, we would say the two countries become even closer; and such increase

8. Garmaise and Natividad (2013) provide evidence on how these political affinity shocks can be traced to various national events that drive the affinity distance between countries farther or closer.

9. The phrasing of the question is: “I would like to ask you a question about how much trust you have in people from various countries. For each, please tell me whether you tend to trust them or tend not to trust them.”

in political affinity would be measured (with noise) by the two countries’ United Nations voting behavior.

Table 3 provides summary statistics of the variables used in the regression analysis.

5. Results

Our main regressions take the form:

$$R_{fj} = \alpha + \beta D_{ij(t-1)} + \theta_{ij} + \lambda_{jt} + \xi_f + \epsilon_{jft} \quad (8)$$

where i is the country where title f is produced and t the year when title f is released. The dependent variable R_{fj} , given by (5), denotes title f ’s release strategy in country j : $R_{fj} = 1$ if release takes place during a high-demand week, zero otherwise. As explanatory variables, we include

- $D_{ij(t-1)}$: the political-affinity shock, as defined by (7) nm
- θ_{ij} : country-interaction fixed effect
- λ_{jt} : country-year fixed effect
- ξ_f : movie title specific effect

We also include a constant α and an error term ϵ_{jft} (country-, movie- and year-specific). The coefficient β thus captures the impact of political affinity shocks on release strategy, after holding various key dimensions fixed.

Propositions 1 and 2 imply a very sharp prediction: the effect of movie appeal on release strategy is opposite depending on whether the movie is a niche movie or a blockbuster. For a blockbuster, the greater the movie’s appeal, the more likely it is released during a high-demand week. In terms of equation (8), this corresponds to $\beta > 0$. By contrast, for a niche movie, the greater the movie’s appeal, the more likely it is released during a low-demand week. In terms of equation (8), this corresponds to $\beta < 0$.

Although Propositions 1 and 2 were cast in terms of extreme values of q (either infinitely small or infinitely large), the numerical simulations in Section 3 suggest that the results hold for “low” and “high” values of q . Our empirical testing strategy is to split our sample into “large” and “small” movies according to various measures.¹⁰ Specifically, we consider movie budget, star case, and number of screens where the movie was released.

Table 4 shows the results for these three possible sample splits. The table includes three pairs of columns, each pair corresponding to a measure of potential movie appeal. In each case, we divide the sample into “top” (the top quintile) and “bottom” (the bottom four quintiles). The regressions include country interaction fixed effects, destination country-year fixed effects, and film dummies. This approach has the advantage of controlling for the enormous heterogeneity across movies and country pairs.

10. One way to interpret Propositions 1–2 is that a relation between the propensity to open during a high-demand week and a measure of movie appeal should be U shaped. This could then be estimated by a flexible, non-linear model relating the two variables. However, given our use of movie fixed effects, we are unable to follow this approach because budget and star power do not vary across different observations of the same movie. The same is not true for number of screens, which vary across country pairs for the same movie. However, among the three measures of potential movie appeal, the number of screens is the variable for which endogeneity issues are the most severe, given the time at which decisions are made.

Overall, the results are quite consistent with Propositions 1 and 2. First, the coefficients corresponding to the top quintile of our sample (according to each of the sorting variables) are positive as predicted by Proposition 2. In words, a positive shock to the appeal in country j of a movie produced in country i implies that the movie is more likely to be released during a high-demand week. As mentioned in Section 2, this is consistent with previous theoretical and empirical results (Krider and Weinberg, 1998; Einav, 2007) that have focused on blockbusters (which we in turn approximate by selecting the top quintile of the sample).

In contrast with the previous literature, all coefficient estimates for the sub-sample corresponding to the bottom four quintiles are negative, as predicted by Proposition 1. In words, a positive shock to the appeal in country j of a movie produced in country i implies that the movie is *less* likely to be released during a high-demand week.

To get an idea of the size of the coefficient estimates, we note that a one-standard deviation increase in the political affinity shock is associated with an increase in high-demand release date of about 5% (blockbusters) or a decrease in high-demand release date of about 2% (niche). That said, we should stress that our goal in these regressions is to confirm the theoretical prediction of the *sign* of the coefficient. Considering the very partial nature of political affinity as a measure of movie appeal, we would not want to assign excessive importance to the magnitude of the coefficient in of itself.

Finally, we note that the coefficient estimates are identified with reasonable statistical significance. Moreover, the fact we obtain similar results with three different measures of potential movie appeal gives us additional confidence in our empirical confirmation of the predictions of Propositions 1 and 2.

■ **Robustness checks.** Considering the centrality of Table 4 in our empirical test, we performed a variety of robustness tests. First, we attempted different ways of splitting the sample between “top” and “bottom”. The signs of the coefficients are fairly robust with respect to different splits. However, the statistical significance of our estimates varies. In particular, when we consider smaller “bottom” samples — for example, the bottom quintile — then we obtain a lower number of observations and an insignificant coefficient estimate.

Much of the prior empirical work on movie releases has focused on US data. Since we are using a global dataset, one may wonder how much of our results depend on extending the analysis to countries outside of the US. In the first two models listed on Table 5 we repeat the regressions in the first two columns of Table 4 by restricting to observations of theatrical release outside of the US. The coefficient estimates are fairly similar to those in Table 4, which suggests the patterns predicted by Propositions 1 and 2 and confirmed by our empirical results are not particular to the US (or outside of the US).

Another robustness check consists in restricting our analysis to large values (in absolute terms) of our independent variable “political affinity shock”. Specifically, the second pair of models listed on Table 5 repeats the regressions in the first two columns of Table 4 by restricting to observations of “political affinity shock” greater than 0.05.¹¹ The signs of the coefficients remain according to theory. However, the statistical prediction of the coefficient estimate corresponding to the top quintile of movie budget is not statistically significant. We note that sample size is reduced to less than 2000 observations.

Finally, in the spirit of Chiou (2008) we consider the possibility that movie characteris-

11. We are grateful to the Co-Editor for this suggestion.

tics such as genre play a role in release-date decisions. Specifically, in untabulated models we find a positive coefficient in the high-demand week release regression restricted to a subsample of “action/adventure” movies and negative coefficient estimate for the complementary subsample. However, we also find that the average budget of an “action/adventure” movie (\$55.2 million) is several times larger than that of other movies (\$16.8 million). This suggests that genre has an effect on release strategy through the propensity for movies in a given genre to be blockbusters. This is also consistent with Chiou’s (2008) evidence that genre per se does not play a significant role in the nature of competition for favorable opening dates.

6. Conclusion

Although our analysis pertains to a very specific industry — the movie industry — we believe our results have broader interest: the movie release game belongs to a wider class of games, namely entry games.

Sometime entry games are modeled as single-market games: the only decision is then whether to enter or not. However, there are also many entry games where, in addition to the entry decision, firms must choose a location as well. Examples include entry games played by multi-store firms such as supermarket chains or franchises such as Burger King.

These particular types of entry games share some of the same features as the movie-release game, namely the tradeoff between potential demand and competition: All things equal, locations with greater demand are more attractive. However, these locations are also likely to attract more competition, which in turn limits their profitability.

Our paper contributes to the analysis of such games by stressing that entry strategies may not be “monotonic” with respect to players’ characteristics. Specifically, unlike supermodular matching games where matching is assortative, we show that the matching between player characteristics and location characteristics may not be monotonic: high demand weekends are preferred by very large blockbusters and by very small niche movies. Whether this pattern applies to other entry games is a question for future research.

Table 1

Results from regressions on pseudo data

Dependent variable: release during high-demand period

	OLS	Probit
Niche movie quality	-0.920*** (0.031)	-2.913*** (0.132)
Blockbuster movie quality	0.002*** (0.001)	0.016*** (0.004)
Constant	0.815*** (0.018)	0.970*** (0.066)
Observations	2000	2000
Adjusted R ²	0.384	

Note: *p<0.1; **p<0.05; ***p<0.01

Table 2

Results from regressions on pseudo data (logit demand)

Dependent variable: release during high-demand period

	OLS	Probit
Niche movie quality	-0.084** (0.036)	-0.184* (0.101)
Blockbuster movie quality	0.005*** (0.001)	0.034*** (0.006)
Constant	0.682*** (0.021)	0.445*** (0.059)
Observations	2000	2000
Adjusted R ²	0.039	

Note: *p<0.1; **p<0.05; ***p<0.01

Table 3
Summary statistics

variable	N	mean	sd	p1	p99
Release on top box office weekend (0/1)	88971	0.14	0.35	0.00	1.00
Political affinity shock	88971	0.00	0.09	-0.20	0.31
Production budget (\$M)	33634	47.65	46.15	0.75	207.00
Actors talent	78919	1.18	1.40	0.00	5.00
Release theaters	30973	309.49	1283.53	1.00	3442.00
Release screens	54585	245.81	835.35	1.00	2629.00

Table 4

Release strategy and political affinity shocks by type of movie (blockbuster vs niche)

Dependent variable: Split:	Release on Top Box Office Weekend (0/1)					
	Top budget	Bottom budget	Top talent	Bottom talent	Top screens	Bottom screens
Political Affinity Shock	0.521** (0.24)	-0.190** (0.08)	0.127 (0.14)	-0.099** (0.04)	0.220* (0.12)	-0.129*** (0.04)
Country interaction fixed effects	Yes	Yes	Yes	Yes	Yes	Yes
Destination country-year fixed effects	Yes	Yes	Yes	Yes	Yes	Yes
Film dummies	Yes	Yes	Yes	Yes	Yes	Yes
Adjusted R^2	0.09	0.06	0.10	0.07	0.10	0.06
N. obs.	5695	25293	10414	58641	15399	60154
N. clusters (release year-week)	483	592	727	728	776	780
N. clusters (country interaction)	365	1101	679	2556	749	2703

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

Table 5

Some robustness tests of release strategy and political affinity shocks results

Dependent variable: Sample:	Release on Top Box Office Weekend (0/1)			
	No U.S. market		Pol. Aff. Shock > 0.05	
Split:	Top budget	Bottom budget	Top budget	Bottom budget
Political Affinity Shock	0.572** (0.26)	-0.178** (0.09)	0.462 (0.32)	-0.542*** (0.15)
Country interaction fixed effects	Yes	Yes	Yes	Yes
Destination country-year fixed effects	Yes	Yes	Yes	Yes
Film dummies	Yes	Yes	Yes	Yes
Adjusted R^2	0.09	0.06	0.11	0.06
N. obs.	5355	23743	1729	8504
N. clusters (release year-week)	478	590	371	535
N. clusters (country interaction)	352	1035	147	336

Note: *p<0.1; **p<0.05; ***p<0.01

References

- BERTRAND, O., BETSCHINGER, M.A., AND SETTLES, A. “The Relevance of Political Affinity for the Initial Acquisition Premium in Cross-border Acquisitions.” *Strategic Management Journal*, Vol. 37 (2016), pp. 2071–2091.
- CABRAL, L. AND NATIVIDAD, G. “Box-Office Demand: The Importance of Being #1.” *Journal of Industrial Economics*, Vol. 64 (2016), pp. 277–294.
- CHIOU, L. “The Timing of Movie Releases: Evidence from the Home Video Industry.” *International Journal of Industrial Organization*, Vol. 26 (2008), p. 1059–1073.
- CRAIG, C.S., GREENE, W.H., AND DOUGLAS, S.P. “Culture Matters: Consumer Acceptance of U.S. Films in Foreign Markets.” *Journal of International Marketing*, Vol. 13 (2005), pp. 80–103.
- EINAV, L. “Seasonality in the U.S. Motion Picture Industry.” *RAND Journal of Economics*, Vol. 38 (2007), pp. 127–145.
- ELBERSE, A. AND ELIASHBERG, J. “Demand and Supply Dynamics for Sequentially Released Products in International Markets: The Case of Motion Pictures.” *Marketing Science*, Vol. 22 (2003), pp. 329–354.
- GARMAISE, M.J. AND NATIVIDAD, G. “Cheap Credit, Lending Operations, and International Politics: The Case of Global Microfinance.” *Journal of Finance*, Vol. 68 (2013), pp. 1551–1576.
- KIM, H. AND JENSEN, M. “Audience Heterogeneity and the Effectiveness of Market Signals: How to Overcome Liabilities of Foreignness in Film Exports?” *Academy of Management Journal*, Vol. 57 (2014), pp. 1360–1384.
- KRIDER, R.E. AND WEINBERG, C.B. “Competitive Dynamics and the Introduction of New Products: The Motion Picture Timing Game.” *Journal of Marketing Research*, Vol. 35 (1998), pp. 1–15.
- NEELAMEGHAM, R. AND CHINTAGUNTA, P. “A Bayesian Model to Forecast New Product Performance in Domestic and International Markets.” *Marketing Science*, Vol. 18 (1999), pp. 115–136.
- SIGNORINO, C.S. AND RITTER, J. “Tau-b or not tau-b: Measuring Alliance Portfolio Similarity.” *International Studies Quarterly*, Vol. 43 (1999), pp. 115–44.
- SIMMONS, B.A. “Rules over Real Estate.” *Journal of Conflict Resolution*, Vol. 49 (2005), pp. 823–848.
- STONE, R.W. “The Political Economy of IMF Lending in Africa.” *American Political Science Review*, Vol. 98 (2004).

TRAIN, K. *Discrete Choice Methods with Simulation, 2nd Ed.* Cambridge University Press, 2009.

VOETEN, E., STREZHNEV, A., AND BAILEY, M. “United Nations General Assembly Voting Data.” (2017).