Learning via Sequential Market Entry: Evidence from International Releases of U.S. Movies*

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Abstract

New products tend to enter foreign markets sequentially. This paper proposes a model in which firms do not initially know the true quality of their products, but in order to enter a new market, the firm must pay a fixed cost. Each firm bases its initial revenue forecasts on country and product characteristics, and each successive release serves to update the firm's expectations for future performance—and thus its decision to enter more markets. On a sample of U.S. movies, I find that a one-standard-deviation increase in the update to expected box-office revenues, based on the previous round of entry, is associated with a 25% increase in the probability of entry to a typical potential destination in the current round.

Keywords: heterogeneous quality; sequential entry; cultural goods trade

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1 Introduction

New products are almost never released simultaneously around the world.[1] Typically, a product will be released domestically and then spread geographically over time. There are a variety of reasons that might lead firms to delay the global distribution of a new product. For instance, firms may choose to delay if domestic success contributes to a positive "buzz", which could be harnessed for international marketing efforts (Elberse and Eliashberg, 2003; McCalman, 2005). Alternatively, if cash-poor firms have private information about the quality of their products, they may not be able to convince creditors to finance international expansion without the proof of robust domestic sales (Chaney, 2005; Manova, 2010; Minetti and Zhu, 2011). Or firms may be uncertain about their own products' profitability (Akhmetova, 2010; Albornoz et al., 2010; Eaton et al., 2011), and thus each subsequent entry could serve to add information about the product's appeal, allowing the firm to update expectations in potential subsequent markets—and avoiding costly entries where they are likely to fail.

At the heart of all three of these explanations is a lack of information, either on the part of consumers, financiers, or the firms themselves. The recent papers cited above exemplify the increased interest in the role of firm learning on the sequential nature of foreign entry. In this paper, I use the motion picture industry to investigate the phenomenon of sequential entry. I document facts about the spatial and temporal patterns of theatrical releases of U.S. movies in key international markets, and propose a model of firm learning. Taking into account the *ex ante* variability of performance within each market as well as the correlations of performance across foreign markets, I find that a one-standard-deviation increase in the update to expected box-office revenues, based on the previous round of entry, is associated with a 25% increase in the probability of entry to a typical potential destination in the current round.

[1]See, for example, Gatignon et al. (1989) and Ganesh et al. (1997) for marketing research on international diffusion by multinationals.

An additional alternative explanation applies to the motion picture industry. If some factors of production are reusable, then staggering entry is a cost-saving exercise. The prints on which films are encoded are expensive, costing about two thousand dollars each.[2] To the extent that they can be reused in multiple countries, delaying international release dates could allow for significant savings. Distributors could release in big markets first and then spread to the smaller markets as prints become available. The marketing effort of the stars—often in the form of local talk-show appearances—is also reusable, and of course by its nature cannot take place simultaneously in distant locales. These tangible examples from Hollywood serve to illustrate more general issues, such as managerial attention to a product release. The alternative explanations of staggered entry do not preclude the strategy that firms use sequential release dates to learn about their product quality. It is possible that all of these concepts are at play. The empirical results of this paper suggest that, even if sequential entry is due to other factors, distributors do learn from their experiences, and act on them by entering more markets on good news and fewer markets on bad news.

There are also forces that would contribute towards simultaneous release dates. Discounting of the future implies firms would rather realize their profits sooner than later. More importantly, delayed foreign release increases the potential for lost sales due to piracy. Distributors face a trade-off between strategically delaying entry, and moving to "day-and-date" simultaneous releases to combat international piracy. If firm learning is an important aspect of staggered release schedules, then the costs of simultaneous international entry could be larger than previously thought.

This paper is related to the nascent literature on exporting and firm learning. Eaton et al. (2011) (EEKKT, hereafter) observe in Columbian transaction-level data that many firms export small amounts and have short tenure as exporters. These facts appear to be inconsistent with the dominant theory of fixed-exporting costs introduced by Melitz

[2] Finney (2010).

(2003). If fixed costs are important, there should be a minimum scale required of exporters in order to break even. EEKKT reconcile the facts with fixed-exporting costs by introducing a search and learning model of trade, in which exporters are initially uncertain of their products' appeal in the foreign market. They estimate their model using the U.S.–Columbia transaction data. Thus, the focus is on learning over time in a bilateral setting. By contrast, the present study considers learning across foreign markets.

Albornoz et al. (2010) (ACCO, hereafter) similarly write a model in which exporters are uncertain about their profitability of exporting. Theirs is a stylized model of two countries and two periods, and emphasizes the value of information from entering one market at a time. The empirical predictions derived from the model are indirect indications of firm learning. ACCO find supporting evidence from a census of Argentinean manufacturers that, conditional on survival, growth rates are highest between the first and second periods in the first export market of the firm. This pattern is consistent with a firm that adjusts its supply upon receiving good news, assuming that the firm can learn almost perfectly after one period. The empirical section of the present study directly tests whether firms respond to past performances by including a Bayesian-derived updating term in an entry regression. Moreover, correlations between markets are not perfect, and differ from one country-pair to another.

Akhmetova (2010) introduces a model in which new exporters can choose a "testing technology", which allows them to export without paying fixed costs, but at a marginal cost that is convex. A second technology exhibits linear marginal costs but requires the payment of a one-time fixed cost of entry. Firms observe noisy signals about their demand during the testing stage. The model endogenizes the length and intensity of the testing stage and—like Arkolakis (2008) and EEKKT—the size of the second-stage entry cost. In choosing the amount of investment in each period, the exporter takes into account the expected revenues that will obtain, but also the value of the information that is learned.

This paper is most similar to ACCO, in that it investigates whether firms sequentially add export destinations as a result of a learning strategy. The "firms" in this study are motion pictures, however, and thus the industry context is quite different. Foreign motion-picture revenue is trade in services (of the actors, directors, editors, etc.), as opposed to the manufacturing trade that was the focus of the other papers. Moreover, movies are cultural products, and thus subject to possibly wide differences in appeal across markets. A necessary condition for firm learning is a positive correlation of appeal in this dimension. ACCO allow for less-than-perfect correlation across markets in an appendix, but focus on the case of single-period (perfect) learning. Furthermore, the life cycle of an individual movie is much shorter than most traded goods. In any given market, a movie will typically play for 4–6 weeks; in the sample of this paper, movies had entered 95% of their ultimate markets within 12 months. Because of these features, firms only make one entry decision per market; there is no scope for intra-market learning.

A key feature of this paper is that I track individual products (movies) and not just firms that may sell multiple products. This is important because the theory relates to the level of demand at the product level. A positive market response to one product may not translate to a firm's other offerings, so it is cleaner to have product-level data. Moreover, the product does not improve over time, as a firm's productivity might, and thus results are not subject to that potential confounding factor. Secondly, in the empirical section I directly test whether past surprises in revenue affect the current probability of further entry. This contrasts with ACCO, who indirectly test learning by separating first-year exporters from experienced (all other) exporters. I am also able to demonstrate the validity of the exercise by showing that future (unrealized) surprises are not nearly as salient as past surprises in explaining entry, which would have indicated that firms do know their true quality—and anticipate the "surprises"—but stagger for other reasons. The results suggest an additional cost to piracy. If distributors move toward simultaneous release in order to thwart pirates, they lose the value of learning-by-staggering, and thus may incur substantial fixed costs even if the movie turns out to have low appeal.

As discussed in the opening paragraph, there is a confluence of factors that inform the international entry strategy of new products. The marketing literature has identified many of these issues for motion pictures,[3] but little attention has been given to the idea that distributors might be using a learning strategy to avoid bad investments. Neelamegham and Chintagunta (1999) propose a Bayesian model of box-office forecasting, in which projections for each movie-destination are updated as new information becomes available. Crucially, however, they treat the decision of whether or not to release a movie in a given country as exogenous. In contrast, I focus on how firms update their expectations in order to inform the entry decision.

The paper proceeds as follows. In section 2 I describe the data set and document features of the spatial-temporal pattern of entry for U.S. movies. In section 3 I derive a model of firm learning that guides the empirical specifications that follow. The regressions suggested by the model are estimated in section 4, along with tests for alternative explanations and other robustness checks. The conclusion summarizes the main findings.

2 Data

Ticket sales revenue by country were collected from the web site boxofficemojo.com. The full sample includes all U.S. movies that were shown in at least one of the other markets considered over the period 2002-2008.[4] Production budget data was taken from the web site the-numbers.com and is available for 761 of the movies. Categorical variables, including the main genre and MPAA rating were obtained from the-numbers.com and

[3]See Elberse and Eliashberg (2003) and Eliashberg, Elberse and Leenders (2006) and the references therein.

[4]The other 13 markets are Argentina, Australia, Czech Republic, France, Germany, Hong Kong, Italy, Japan, Netherlands, New Zealand, Norway, Spain, and United Kingdom.

imdb.com, respectively.

Figure 1 graphs for each country the number of movies imported versus the average box-office revenue in the market. Countries with the most entries are English-speaking (Australia and UK) or large (Germany). Nevertheless, Spain is the second-most-preferred foreign destination. The markets with the least number of entries are culturally-distant Hong Kong and Japan, both of which also have thriving domestic film industries. In general, countries with higher average revenues also import more films. Japan is a large outlier, as it is the second-least-preferred market but is the highest performer for the movies that do enter. This might be due to large entry costs for the Japanese market. With large entry costs (e.g. print and advertising costs), only the higher-grossing movies will find it profitable to enter, thus increasing the average box-office revenue in the country and decreasing the total number of entrants. For the other countries in the sample, it seems that the market size effect dominates this selection effect. All movies tend to do better in bigger markets, so even though this means low-quality movies may enter, average revenues increase in the number of entrants because both are driven by the large market.

Epstein (2005) breaks down the costs of foreign entry for the movie, *Gone in Sixty Seconds* (2000). The figures are presented in Table 1. Advertising costs are given by country for seven important foreign markets, and other costs are provided in aggregate form. The table confirms Japan is a high-cost market, with advertising costs more than twice as high as the next most costly country. The table also demonstrates how costly foreign entry is. More than half the box-office revenue of $129.5 million is taken by exhibitors, and after paying expenses, the total profit left for the distributor, Disney, is just $18 million. Epstein (2005) also provides the example of Clint Eastwood's *Midnight in the Garden of Good and Evil*, which earned $3.1 million at the foreign box office, but cost $6 million in foreign prints and advertising. He notes that many releases lose money

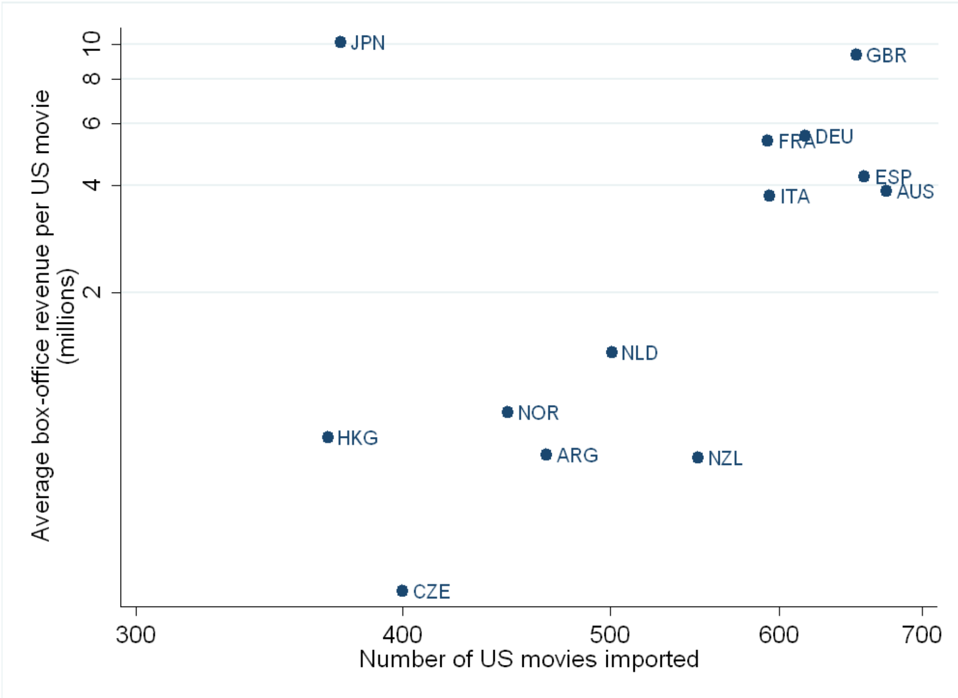

Figure 1: Intensive vs. Extensive Margins of Entry

abroad.

Figure 1 shows that there is wide variation at both the extensive and intensive margins of entry. To understand which films are traveling abroad, consider Figure 2, which plots the number of markets a movie enters against its domestic box-office revenue. Better-performing movies tend to enter more foreign markets, and the relationship is tighter for the non-comedy-drama genres. While there is considerable noise at the disaggregated movie level, Figure 3 shows that, when movies are aggregated according to the number of markets they entered, there is a monotonic relationship between the number of markets and the mean domestic revenue.

Figures 2 and 3 tell us about the long-run pattern of entry. Not surprisingly, the more appealing a movie is to audiences—as measured by domestic box-office returns—the more countries that movie is likely to enter. This result is natural if destination-specific fixed costs are important. Then only those movies that are likely to earn enough at the box-

Table 1: Costs of Foreign Entry: *Gone in Sixty Seconds*

	JPN	DEU	GBR	FRA	AUS	ESP	ITA	Other	Total
Advertising	6.5	3.1	2.5	1.4	1.1	1.0	0.9	8.7	25.2
Prints									5.7
Dub/Subtitle									0.82
Shipping									0.46
Foreign Taxes									5.0
Curr. Conv.									0.27
For. Trade Assoc.									0.12
Total Costs									38.0
Exhibitors' Share									73.5
Total Deductions									111.5
For. Box Office									129.5
Foreign Profit									18.0

All figures in millions of U.S. dollars
Source: Epstein (2005)

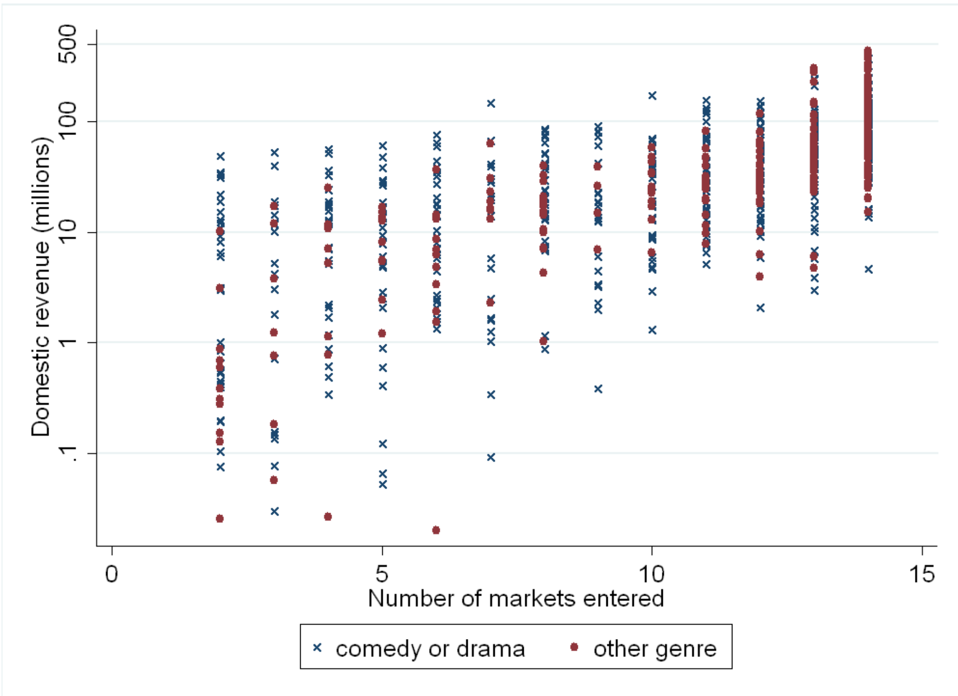

Figure 2: Domestic Revenue vs. Number of Markets Entered

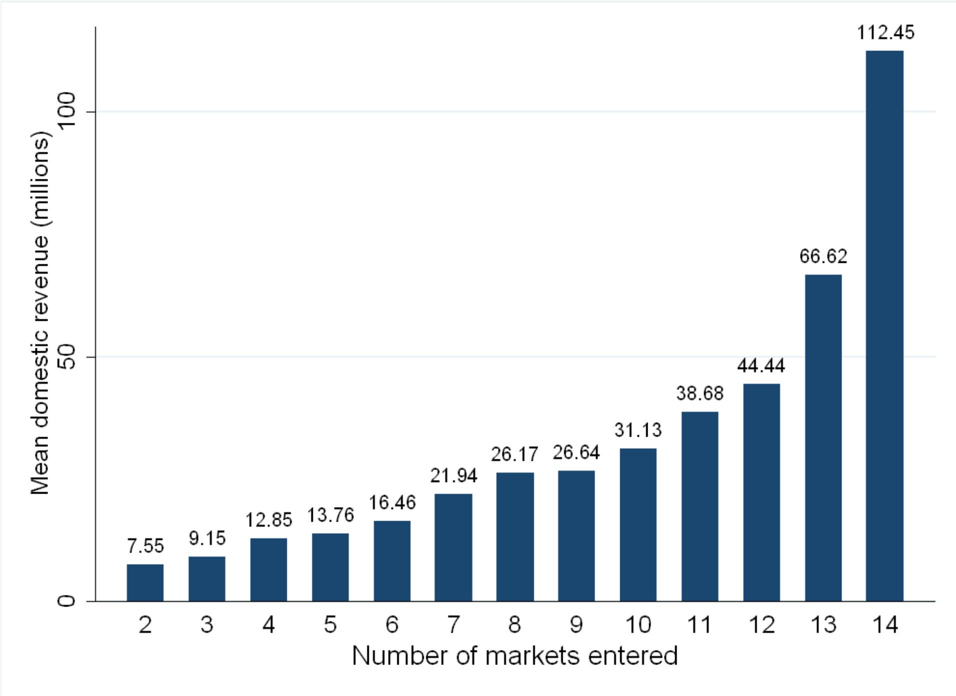

Figure 3: Mean Domestic Revenue by Number of Markets Entered

office to offset these costs will enter a foreign market. As long as returns are correlated across the domestic and international markets, we expect the positive relationship that we observe.

Studios and distributors can't forecast precisely how well a movie will perform before it is released, but they can make reasonable predictions. Domestic revenues are correlated with the production budget, as shown in Figure 4. Apart from a few low-budget surprise successes, the budget does quite well in predicting performance, with an R^2 of 0.43.[5] If firms are using a sequential entry strategy because of uncertainty about the profitability of their products in each market, it seems less likely that they would do so when the production budget (and thus, expected profit) is high.

Indeed, big-budget blockbusters are far more likely to have near-simultaneous release dates internationally. The median delay to foreign release since the U.S. premiere is de-

[5]The linear fit displayed in the figure is calculated by omitting the movies with a budget of less than $100,000. The OLS slope-coefficient is 0.84; with the low-budget movies included it is 0.74.

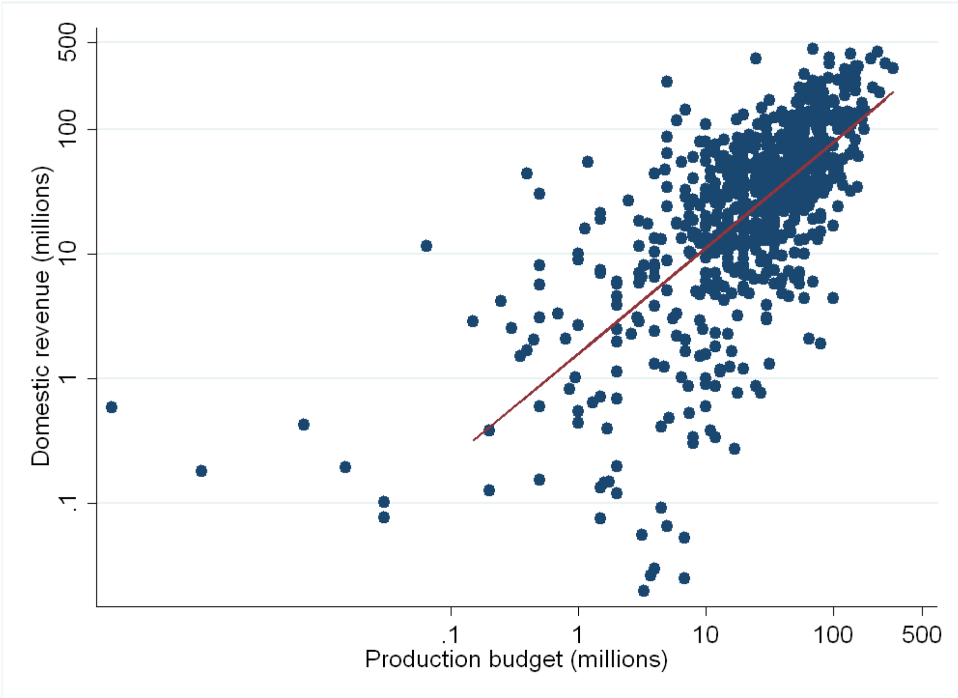

Figure 4: Domestic Box-Office Revenue vs. Production Budget

creasing in the size of the budget (Figure 5), despite the fact that big-budget movies enter *more* markets. Considering the quartiles of production budget in turn, the histograms of median delay are increasingly skewed towards early release (Figure 6). This might be a reaction to movie piracy, but it also demonstrates the confidence that firms have in recouping their entry investments. Distributors of smaller productions might test the popularity of their products one market at a time, expanding with good news or limiting distribution if profitability is allusive. To illustrate, Figure 7 charts the entry dates and performance (relative to initial prediction) of the 2003 Woody Allen production, *Anything Else*. With a budget of $18 million, it sits in the second quartile of the sample. In the first month, the movie disappointed in the U.S. but was a surprise success in Italy. The film then spread to France and Spain where it also played well. Three months later it was released in Argentina, to a neutral performance, before stumbling in Northern and Eastern Europe. It did not enter the remaining five markets in the sample. Figure 8 illustrates

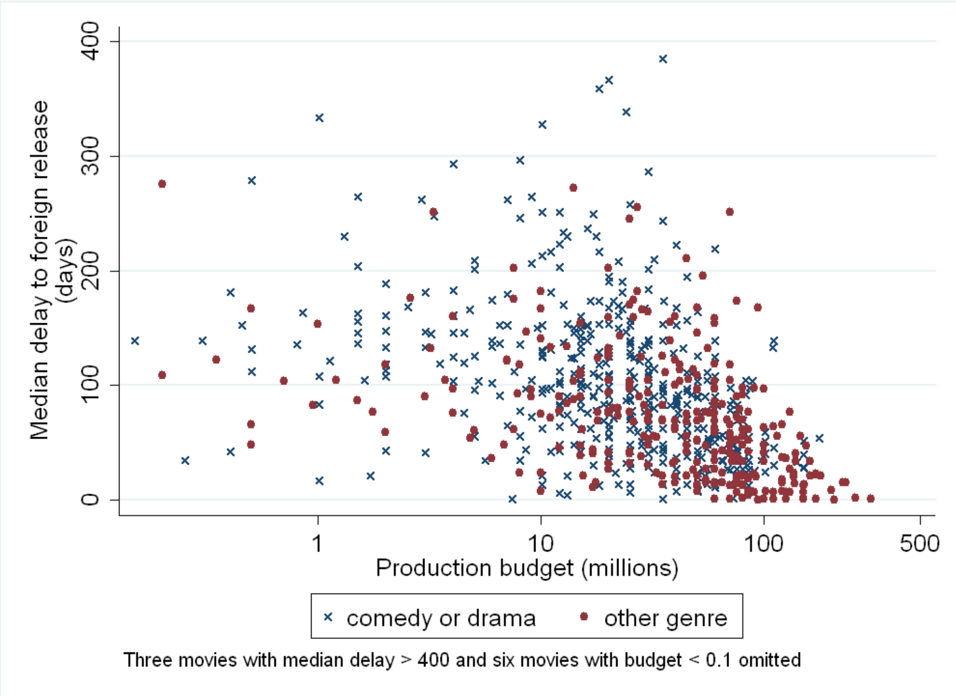

Figure 5: Median Delay vs. Production Budget

the entry timing and performance of the 2007 Quentin Tarantino horror, *Grindhouse*. Its budget of $45 million puts it in the third quartile, but poor performance in all four of its first markets appears to have limited further international releases.

Apart from the Italian release of *Anything Else*, which occurs in the same month as that of the U.S., Figures 7 and 8 exemplify a pure sequential entry pattern: each country was entered in a separate month. To illustrate another entry pattern, consider Figure 9, which plots the entry dates and performance for the 2004, seventy-five-million-dollar comedy, *50 First Dates*, starring Adam Sandler and Drew Barrymore. Here we see a mix between sequentiality and simultaneity, with multiple countries entered in each month. To capture the degree to which a movie is released according to a sequential entry strategy, I compute a "sequential index" for each movie. First, I partition the release dates into months since the U.S. release (with month 1 indicating the month of the U.S. release). Any country that is entered in the same month as another is considered to be entered

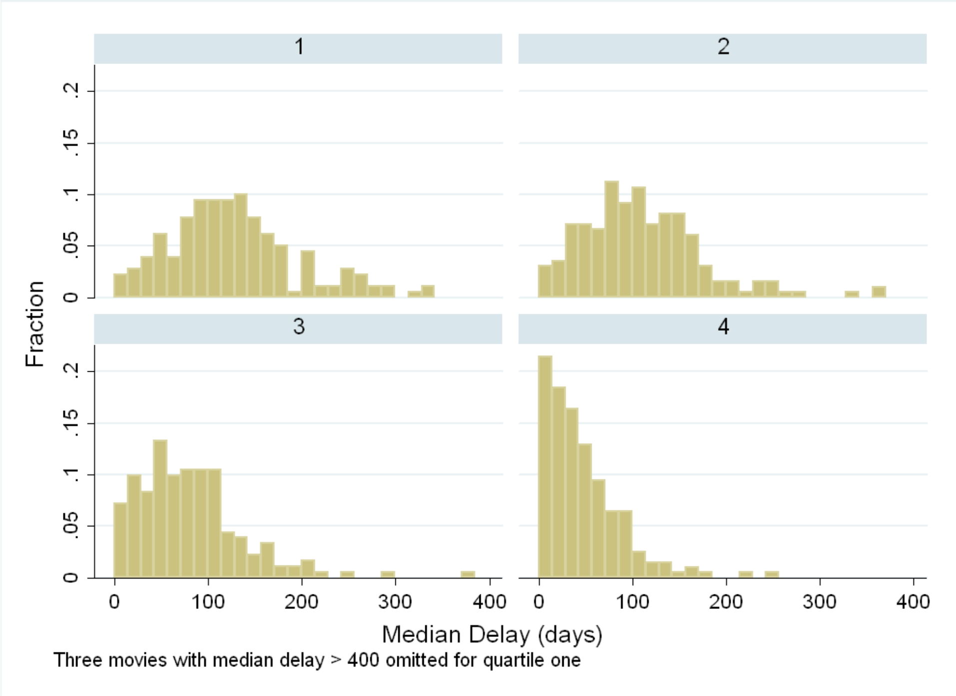

Figure 6: Histogram of Median Delay by Production Budget Quartile

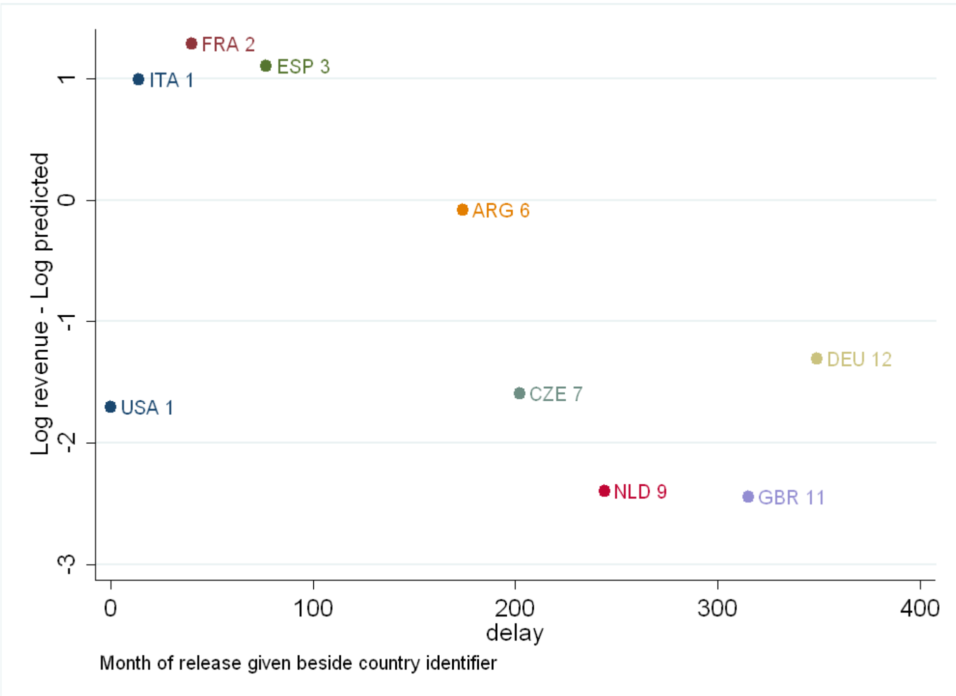

Figure 7: Entry Timing and Performance of “Anything Else”

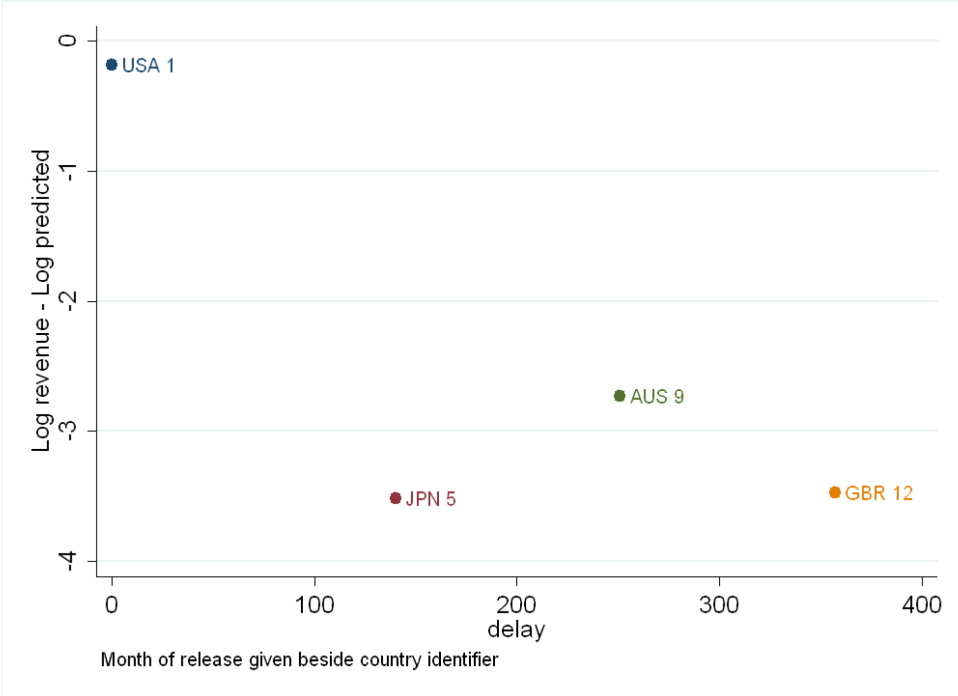

Figure 8: Entry Timing and Performance of “Grindhouse”

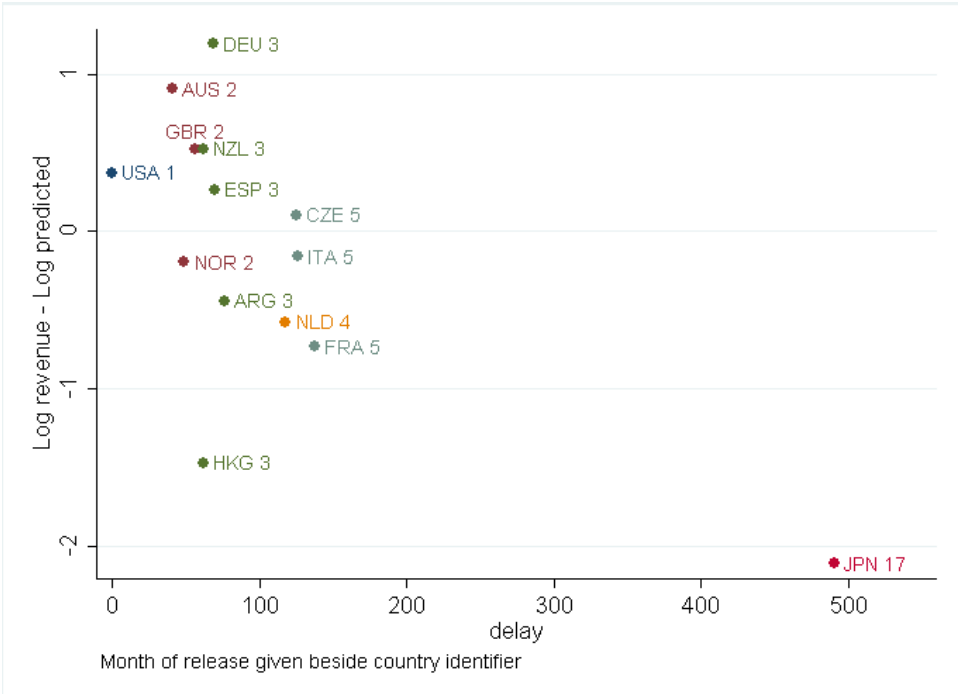

Figure 9: Entry Timing and Performance of “50 First Dates”

simultaneously with that other country. For most movies, there are gaps in the month in which new entry occurs. For example, a movie might go to two markets in month one, three markets in month two, but then only enter its last market in the fifth month. I refer to months in which the movie does enter new markets as "rounds" of release, so for this hypothetical movie, the fifth month would be considered round three. The sequential index, Z, is computed as follows:

$$Z = \frac{N_{rounds} - 1}{N_{markets} - 1}, \tag{1}$$

where N_{rounds} is the number of rounds of release and $N_{markets}$ is the total number of markets entered for each movie. The index gives the ratio of the number of extra rounds taken to the number of foreign markets entered. Thus, if the movie enters ten countries and takes ten rounds of release to do so, the fraction is one, and this movie is characterized by pure sequential entry. If the movie entered all ten countries in one round, the fraction would be zero, indicating pure simultaneous entry. Interior values indicate the degree to which the movie followed a sequential entry strategy. For example, consider a movie that entered five markets. If it did so in three rounds, the index is $(3-1)/(5-1) = 0.5$, reflecting the fact that a mix of simultaneous and sequential entry is observed.

Figure 10 provides a histogram of the sequential index. It shows a large spike at one, reflecting the fact that more than one hundred of the movies exhibit pure sequential entry. Just twenty of the movies were released according to a pure simultaneous strategy (all within a month of the U.S. release). The remainder fall somewhat symmetrically around a value of one half, with a small spike around the 0.2 mark.

We have established that movies with large production budgets tend to diffuse internationally more quickly. The longer delay for low-budget movies could be due to sequential entry, or it could occur if they are delaying all their foreign releases for some time, and

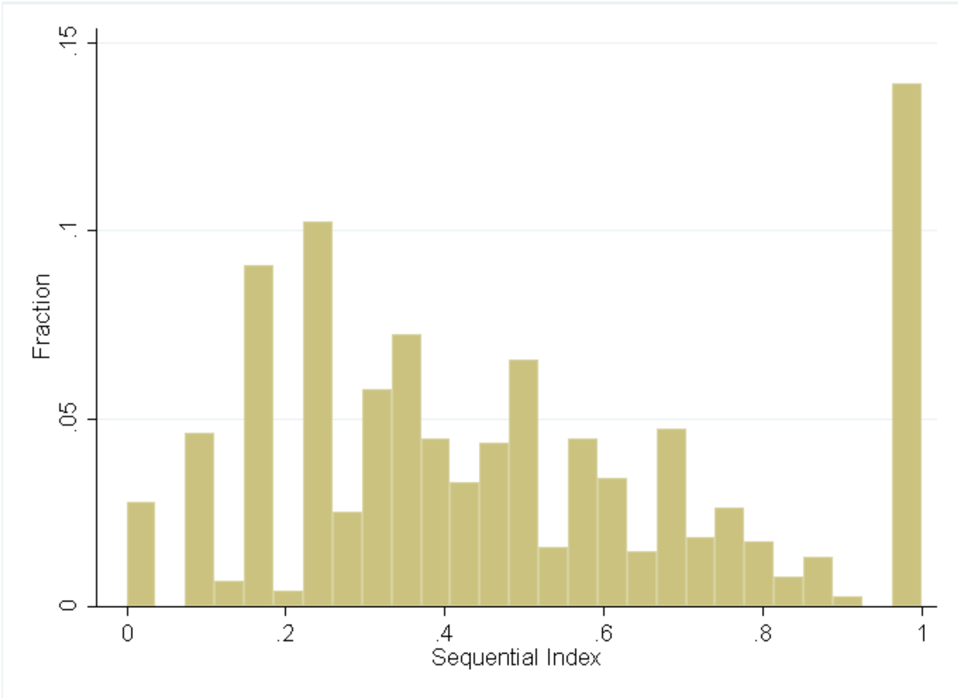

Figure 10: Histogram of Sequential Index

then entering them all simultaneously. To investigate which movies are indeed entering sequentially, Figure 11 plots the sequential index against the production budget, along with a Lowess smoother. The figure confirms that low-budget movies do in fact employ a greater degree of sequential entry than their big-budget counterparts. Moreover, the effect is not driven by differences in budget by genre type, although comedies and dramas do show a higher propensity for sequential entry at any given budget level. This makes sense given their lower appeal in foreign markets.

In addition to looking at which types of movies tend to be sequentially released, we can investigate the order in which countries tend to be entered. The simplest measure of this is the average round of release among a country's imported movies. Figure 12 plots this value for each of the 13 foreign markets. Note that the four destinations with the lowest average round of entry are all English-speaking. Figure 13 plots the average round of entry against the correlation between the countries' box-office revenues and those of

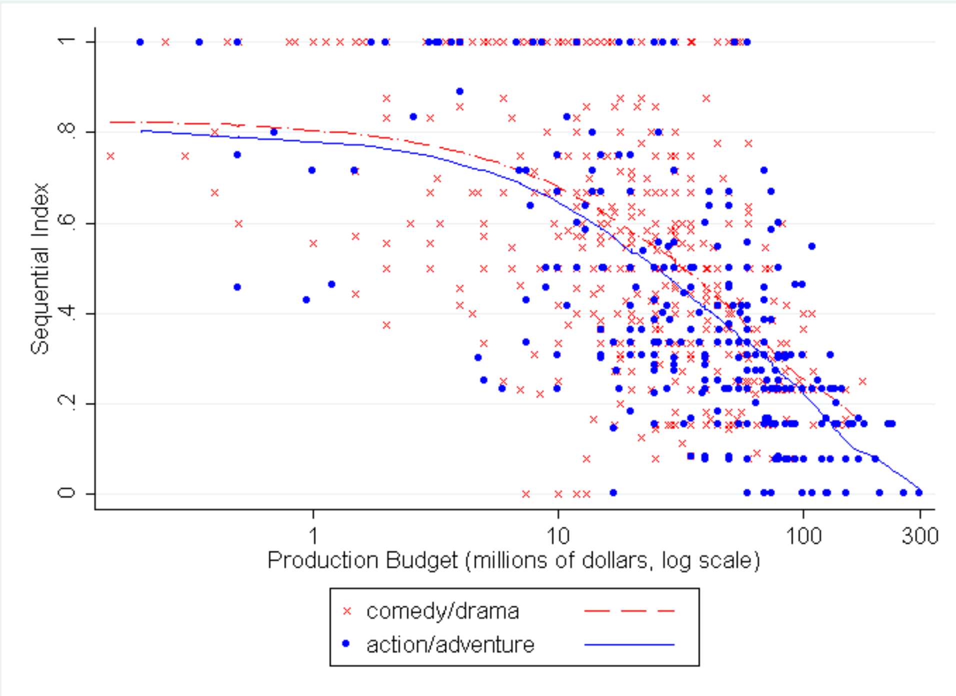

Figure 11: Sequential Index vs. Production Budget

the U.S.. On average, countries with closer agreement to the U.S. are entered in earlier rounds than countries with less agreement. Both the average rounds of entry and the box-office correlations with the U.S. could be affected by selection. As a robustness check, Figure 14 reproduces the plot where only information from the 202 movies that entered all 14 markets is used. The relationship between average round of entry and correlation with the U.S. persists, and appears stronger. Australia and New Zealand become earlier markets than Hong Kong for this sample, while France, Germany and Spain move up relative to the Netherlands and Norway.

The data patterns illustrated in this section are consistent with the idea that firms that are uncertain about their export profitability may use sequential entry to learn and update expectations. The next section introduces a model that encompasses this idea and provides estimating equations to take to the data. Section 4 presents the methodology for operationalizing the model, and reports results of directly estimating the effect of a

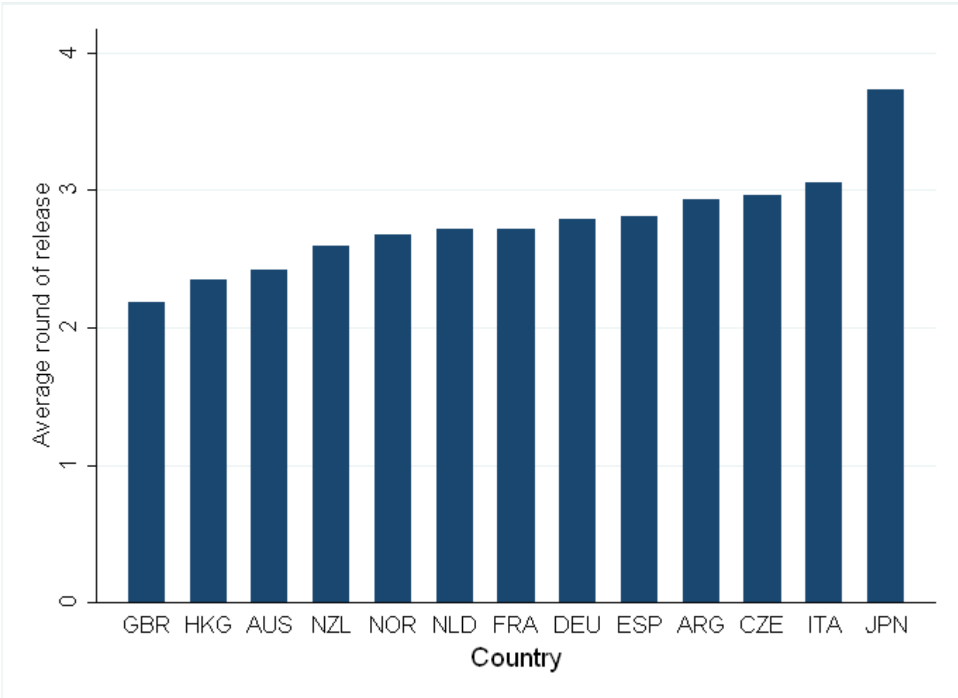

Figure 12: Average Round of Release by Country

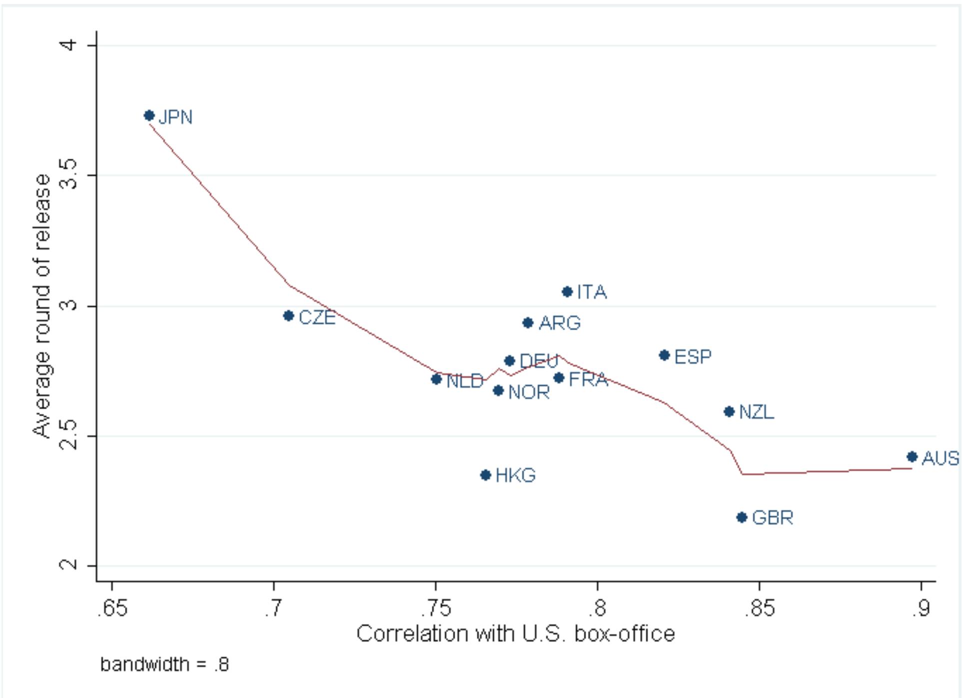

Figure 13: Average Round of Release vs. Correlation with U.S. Box-Office

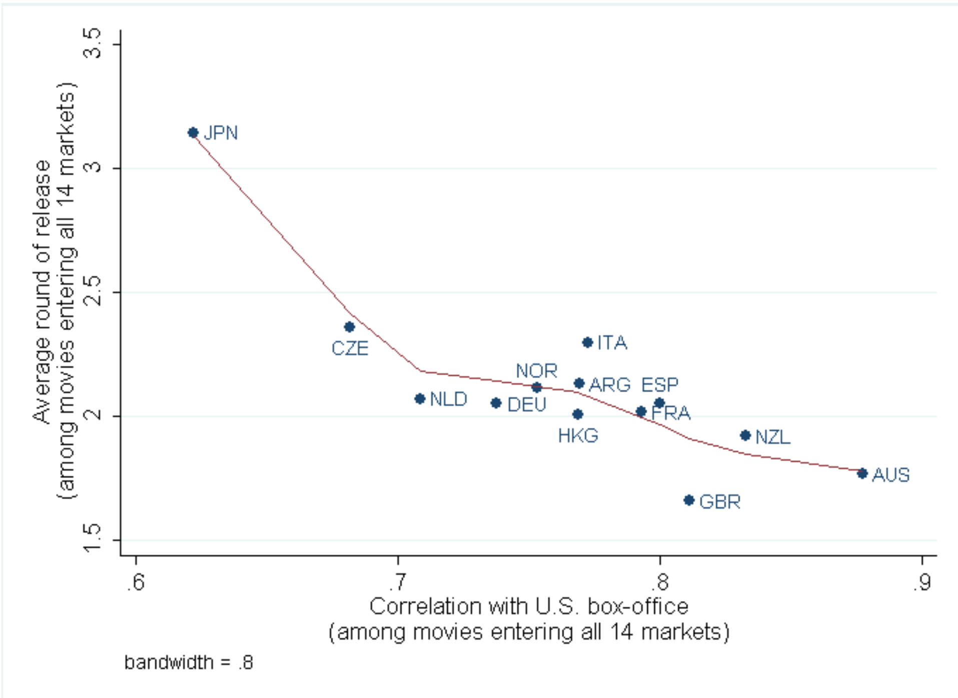

Figure 14: Average Round of Release vs. Correlation with U.S. Box-Office: subsample of movies going to all markets

performance surprise on the probability of further entry.

3 Theory

Consider a risk-neutral firm making entry decisions in K segmented markets. To enter any of the destination markets, indexed by d, firm m must incur a per-destination fixed cost of F_{dm}, corresponding to print and advertising costs.

Movies are heterogeneous in their appeal, which is not directly observable even by their distributors. The appeal of any given movie also varies between markets, due to country-specific idiosyncracies in taste. Holloway (2011) introduces a discrete choice model in which revenues for different varieties of a product (e.g. different movies) depend on country- and variety-specific terms multiplicatively, in addition to a multiplicative idiosyncratic factor. The derivation follows.

Individuals in country d purchase a variety of the product if their valuation of doing so is greater than the price, p_d, which varies between countries but not within each country. Prices are taken as given in each market. The valuation of individual i from destination d consuming variety m is:

$$v_{idm} = k(\beta q_m + \psi_{dm} + U_{idm})n(y_d), \tag{2}$$

where q_m is the average perceived quality of the variety, ψ_{dm} is the country-variety taste shock, U_{idm} is the individual's idiosyncratic utility, y_d is the income per capita in country d and the functions $k(\cdot)$ and $n(\cdot)$ are increasing and could be destination-country specific. The parameter β adjusts for the scale on which quality is measured. Valuation is separable in per capita income, reflecting the higher willingness-to-pay in rich countries for any given quality level.

Revenues from exporting to country d are given as the product of the price and the number of people who purchase the variety. This latter quantity can be expressed as the product of the total population and the proportion of the public who purchase:

$$R_{dm} = p_d M_d \mathbb{P}[v_{idm} > p_d], \tag{3}$$

where M_d is the population of country d and the proportion of the purchasing public is replaced by the probability that any of the (symmetric) individuals in the country will purchase.

Plugging 2 into 3,

$$\begin{aligned}
R_{dm} &= p_d M_d \mathbb{P}[k(\beta q_m + \psi_{dm} + U_{idm}) n(y_d) > p_d] \\
&= p_d M_d \mathbb{P}[\beta q_m + U_{idm} + \psi_{dm} > k^{-1}\left(\frac{p_d}{n(y_d)}\right)] \\
&= p_d M_d \mathbb{P}[U_{idm} > k^{-1}\left(\frac{p_d}{n(y_d)}\right) - \beta q_m - \psi_{dm}] \\
&= p_d M_d (1 - \mathbb{P}[U_{idm} < k^{-1}\left(\frac{p_d}{n(y_d)}\right) - \beta q_m - \psi_{dm}])
\end{aligned} \tag{4}$$

If U_{idm} is distributed exponentially with parameter λ, then the above reduces to:

$$R_{dm} = p_d M_d e^{\lambda + \beta q_m + \psi_{dm} - k^{-1}\left(\frac{p_d}{n(y_d)}\right)} \tag{5}$$

Define the attractiveness of country d as $A_d \equiv p_d M_d e^{\lambda - k^{-1}\left(\frac{p_d}{n(y_d)}\right)}$ and let $Q_m \equiv e^{q_m}$ and $\Psi_{dm} \equiv e^{\psi_{dm}}$. We can then express the revenue equation succinctly as

$$R_{dm} = Q_m^{\beta} A_d \Psi_{dm}. \tag{6}$$

Taking the logarithm of equation (6) gives the linear equation,

$$r_{dm} = \beta q_m + a_d + \psi_{dm}, \tag{7}$$

where lower-case letters represent logarithmic terms and $\psi_{dm} \sim N(0, \sigma^2_\psi)$.

Although the quality of the movie is not known *ex ante*, there are known imperfect proxies. A firm might make reasonable predictions about future revenues in each of the prospective markets by substituting the known proxies in for unknown quality, and using historical data to estimate country fixed effects—to substitute for a_d—and the parameter β. That is, if the firms know the "law of revenues", they can substitute in their quality proxies to make initial predictions about potential revenues in each of the markets. In particular, suppose that quality, q_m, is a function of the logarithm of the movie's budget, $b_m = \ln B_m$:

$$q_m = \alpha b_m + \xi_m, \tag{8}$$

where $\xi_m \sim N(0, \sigma^2_\xi)$. Substituting equation (8) into (7), and replacing a_d by a set of destination fixed effects gives[6]

$$r_{dm} = \beta\alpha b_m + a_d + \nu_{dm}. \tag{9}$$

where $\nu_{dm} = \beta\xi_m + \psi_{dm}$.

Firms form beliefs for each market according to equation (9).[7] The normality assumptions on ξ and ψ—and thus on ν—imply a normal prior: $r_{dm} \sim N(\mu_{dm1}, \sigma^2_{d1})$, where

$$\begin{aligned} \mu_{dm1} &= \beta\alpha b_m + a_d \qquad (10) \\ \sigma^2_{d1} &= \sigma^2_{\nu_d}. \qquad (11) \end{aligned}$$

For clarity of exposition, let us assume there are only three destinations, A, B, and C. All movies enter market A but the firms can choose whether or not to enter B and C. After the first period, firms update their expectations about log revenues, r_{dm}, in the

[6] By an abuse of notation, I am calling the destination-specific constant (fixed effect), a_d, which is not equal to the conceptual $\ln A_d$.

[7] That is, firms know the value of the compound parameter $\beta\alpha$ and the destination-specific constants.

remaining potential markets, $d \in \{B, C\}$, using realized revenues in market A. According to Bayes' Law, $r_{dm2} \sim N(\mu_{dm2}, \sigma^2_{dm2})$ with

$$\mu_{dm2} = \mu_{dm1} + \rho_{Ad}\frac{\sigma_{d1}}{\sigma_{A1}}(r_{Am} - \mu_{Am1}) \tag{12}$$

$$\sigma^2_{dm2} = \sigma^2_{d1}(1 - \rho^2_{Ad}) \tag{13}$$

where ρ_{Ad} is the correlation between ν_{Am} and ν_{dm}, σ_{d1} is the square root of $\sigma^2_{\nu_d}$, and $(r_{Am} - \mu_{Am1}) \equiv \nu_{Am}$ is the difference between the realized and expected log revenues for movie m in country A.

These Bayesian updating formulas provide intuition for how predictions in future potential markets depend on the surprises observed in entered markets. The surprises are tempered by the degree of correlation across the two countries, and the degree of variation within each of the countries. The posterior variance is always decreased after new information is attained, but again the amount of precision gained depends on the correlation between the markets involved.[8]

The model abstracts from the informational value of entering and is thus a model of "passive" learning. The movie will enter market d if the expected profit from doing so is positive. Recall that a fee of F_{dm} is required for movie m to enter market d. Assume that $F_{dm} = K_d\zeta_{dm}$, where K_d is destination-specific but ζ_{dm} is movie-destination-specific and is unobservable to the econometrician, though known to the firms. Letting $\mathcal{E}_{dmt}$ denote the indicator function for entry of m into d in period t, the probability that movie m will

[8] In practice, movies enter more than one country per period. To aggregate the surprises in each of the entered markets, a matrix version of Bayes' Law is required. It is introduced in section 4.1.

enter destination d is[9]

$$\begin{aligned}
\mathbb{P}[\mathcal{E}_{dmt}=1] &= \mathbb{P}[\mathbb{E}_t[R_m^d - F_{dm}] > 0] \\
&= \mathbb{P}[\mathbb{E}_t[R_m^d] > K_d\zeta_{dm}] \\
&= \mathbb{P}[e^{\mu_{dmt}+\frac{\sigma_{dmt}^2}{2}} > K_d\zeta_{dm}] \\
&= \mathbb{P}[\mu_{dmt}+\frac{\sigma_{dmt}^2}{2} > logK_d + log\zeta_{dm}] \\
&= \mathbb{P}[log\zeta_{dm} < \mu_{dmt}+\frac{\sigma_{dmt}^2}{2} - logK_d] \\
&= \mathbb{P}[log\zeta_{dm} < \mu_{dm,t-1}+s_{dm,t-1}+\frac{\sigma_{dmt}^2}{2} - logK_d], \qquad (14)
\end{aligned}$$

where $s_{dm,t-1}$ is the update based on last period's performance.

Note that the variance terms become movie specific after the first period. This is because not all movies enter countries in the same order. Since the updated variance depends on the correlation coefficient between the country in consideration and the country of last entry, the variance terms will differ if the country of last entry differs. In the simple three-country example, country B for one movie may be country C for another.

4 Results

The model predicts that surprises in box-office revenue in previous markets affect the probability of entry into potential future markets. I test this prediction using regression analysis and consider alternative explanations for the results.

4.1 Firm learning and the decision to enter

First it is necessary to construct the appropriate variables, in particular the update to movie m at time t. Recall from the model that, initially, distributors form expected

[9]If $\log(X) \sim \mathrm{N}(\mu, \sigma^2)$ then $X \sim \text{Log-N}(\mu, \sigma^2)$ and $\mathbb{E}X = e^{(\mu+\frac{\sigma^2}{2})}$.

revenues for each potential destination based on movie characteristics such as the budget, and destination characteristics such as the country's historical expenditure on movies. I form *ex ante* predicted revenues for each movie-destination pair by regressing *ex post* actual (log) revenues on the movies' (log) budget and destination fixed effects. I allow the coefficient on budget to differ across the destinations and augment the equation with interactions between country dummies and genre and MPAA-rating dummies:

$$\ln R_{dm} = \alpha_d \ln B_m + \{FE_d\} \times \{\text{GENRE}_m\} + \{FE_d\} \times \{\text{MPAA}_m\} + \{FE_d\} + \epsilon_{dm}. \quad (15)$$

I then set the first-period predicted log revenues, μ^1_{dm}, equal to $\widehat{\ln R_{dm}}$.

Time periods are based on the month since the U.S. release. Although I have data on the precise day on which a movie was released in any given market, it is impractical to use days as the unit of time. Using daily time periods would introduce a lot of noise since there may be many idiosyncratic reasons for releasing on one day rather than the next. Recalling that the benefit to "pulling the plug" on a release is the saved fixed costs, the incentive to do so decreases as the period between learning that the movie will not make money in the market and the release date narrows. This is because advertising costs are sunk once they are spent. Similarly, adding a new market based on good performance would take time to organize and promote. I set the unit of time to be a month (30 days), but robustness checks show the qualitative conclusions are unaffected by changing this window.

For most movies, there are gaps in the month in which new entry occurs. For example, a movie might go to two markets in month one, three markets in month two, but then only enter its last market in the fifth month. According to the updating theory, there is no explanation for the delay in entry to the fifth month. The same information was available in the third and fourth months. Indeed, the model is about information sets and not time. Accordingly, I collapse the data to the level of information sets—or *rounds* of entry—rather than keep all possible months for each movie. Thus, for the hypothetical movie above, only observations corresponding to months one, two, and five would be kept. A final set of observations represents the round after the last new entry has taken place. It is important to include since it is informative that none of the remaining potential markets imported the movie in this last information set. This procedure highlights the fact that we are not trying to explain the magnitude of the delay to foreign release, but rather to test whether new information affects the decision to release.

I compute the expected revenues and surprises for each destination-movie-round triple using an iterative procedure. The updating equations of section 3 apply if only one country is entered per period. In practice, many movies enter multiple countries per round and the surprises from each entered country must be aggregated to form the update for each remaining potential market. To do this we can employ the matrix versions of the Bayesian updating equations. Denote the set of countries entered in period $t-1$ by Y and the set of remaining potential destinations X.[10] The updating equations become:

$$\mu_X^t = \mu_X^{t-1} + \Sigma_{XY}^{t-1} \left(\Sigma_{YY}^{t-1}\right)^{-1} \left(r_Y - \mu_Y^{t-1}\right) \tag{16}$$

$$\Sigma_{XX}^t = \Sigma_{XX}^{t-1} - \Sigma_{XY}^{t-1} \left(\Sigma_{YY}^{t-1}\right)^{-1} \left(\Sigma_{XY}^{t-1}\right)', \tag{17}$$

where μ_X^t and μ_Y^t are vectors of predicted log revenues going into period t for the sets X and Y, respectively, r_Y is the vector of realized log revenues in Y, Σ_{XX}^t and Σ_{YY}^t are variance-covariance matrices, and Σ_{XY}^{t-1} is a cross-covariance matrix. All initial variance and covariance elements are calculated from the residuals, ϵ_{dm}, from equation (15).

Table 2 provides correlation coefficients of ϵ_{dm} for each country pair. On the main diagonal, the variance of the residuals within each country is reported. The upper triangle reports Pearson correlation coefficients, which describe the strength of the linear relation-

[10] These sets of course depend on the movie, m, and the period, t, but the subscripts are omitted for convenience of exposition. Note that the set of destinations entered before $t-1$ is irrelevant to the calculations since information from these entries is already incorporated into the $t-1$ prior.

ships, and are directly related to the covariances between countries. The country-pair with the highest correlation is Australia–New Zealand, at 0.768, followed by Australia–United Kingdom (0.744) and Netherlands–Norway (0.743). The country-pair with the lowest correlation is France–United States, at 0.396. The next three lowest correlations also involve the United States, paired with Spain and Italy (each at 0.402) and Japan (0.414). In general, the correlations point to regional and colonial groupings: there are high correlations among Northern European and North American markets (U.S. statistics include box-office revenue in Canada); Mediterranean European countries exhibit high correlation among themselves; the market in most agreement with Japan is Hong Kong; Argentina's ties to Spain and Italy are reflected, although its second highest correlation is surprisingly with Hong Kong. The lower triangle reports Kendall's tau, which provides a non-parametric measure of concordance of the ranking of movies for each country pair. The same general patterns of association are uncovered through this alternative measure.

Table 2: Correlations of Residuals between Markets

	ARG	AUS	CZE	DEU	ESP	FRA	GBR	HKG	ITA	JPN	NLD	NOR	NZL	USA
ARG	**1.32**	0.526	0.537	0.554	0.660	0.557	0.496	0.592	0.583	0.448	0.518	0.550	0.511	0.475
AUS	0.398	**2.53**	0.507	0.703	0.633	0.628	0.744	0.532	0.521	0.452	0.698	0.630	0.768	0.635
CZE	0.385	0.415	**1.37**	0.619	0.492	0.554	0.585	0.583	0.515	0.440	0.572	0.618	0.554	0.479
DEU	0.403	0.573	0.472	**2.74**	0.715	0.701	0.719	0.528	0.665	0.510	0.695	0.677	0.647	0.546
ESP	0.478	0.474	0.363	0.523	**2.60**	0.736	0.613	0.487	0.707	0.460	0.589	0.576	0.477	0.402
FRA	0.416	0.489	0.416	0.541	0.535	**2.98**	0.608	0.510	0.730	0.502	0.645	0.653	0.560	0.396
GBR	0.387	0.625	0.444	0.575	0.455	0.514	**2.40**	0.540	0.559	0.513	0.714	0.666	0.733	0.614
HKG	0.430	0.380	0.412	0.383	0.335	0.362	0.401	**1.27**	0.459	0.591	0.533	0.523	0.530	0.445
ITA	0.447	0.428	0.399	0.500	0.565	0.584	0.450	0.338	**3.28**	0.468	0.556	0.599	0.497	0.402
JPN	0.347	0.357	0.356	0.382	0.337	0.385	0.373	0.419	0.372	**2.26**	0.441	0.454	0.469	0.414
NLD	0.400	0.541	0.459	0.569	0.444	0.507	0.563	0.393	0.431	0.365	**1.84**	0.743	0.656	0.629
NOR	0.415	0.500	0.480	0.521	0.421	0.487	0.527	0.397	0.445	0.366	0.569	**2.01**	0.637	0.584
NZL	0.372	0.638	0.431	0.491	0.368	0.451	0.560	0.398	0.380	0.359	0.491	0.496	**1.13**	0.582
USA	0.334	0.540	0.365	0.455	0.337	0.358	0.502	0.349	0.330	0.341	0.488	0.439	0.469	**1.48**

Pearson correlation coefficients on upper triangle; Kendall's tau on lower triangle; variances on main diagonal

Table 3 reports the main result of the study. Each specification estimates the probability that a movie enters a destination in a given round, conditional on the movie not being released there previously. The table reports standardized average partial effects, so that it presents the change in the probability of release induced by a one-standard-deviation increase of the variable in question. The first column estimates the degree to which current expected revenue affects the decision to release. The first round of releases is excluded from the regression because this specification acts as a benchmark for the other columns, which include lagged variables. The coefficient implies that a one-standard-deviation increase in the (log) predicted revenue increases the probability of entry in the current period by 14.8 percentage points, compared to an average probability of 21.3%. As predicted, expected revenue makes a big difference in the decision to release a movie in a given country.

The second specification examines the constituent parts of the expected revenue, namely the expected log revenue in the previous round plus the update from the previous period. If firms do not adapt their entry strategies based on information learned in period $(t-1)$ then we should not expect the coefficient on the update to be significant. In fact, the coefficient implies that a one-standard-deviation increase in the previous round's update is associated with a 5.0 percentage-point increase in the probability of entry. This is an increase of more than 23% over the average probability of entry. Column 3 includes interactions between the update and dummies for the first period and all other periods. This specification checks whether firms are learning only after the first round of entry, or whether subsequent entries also affect entry decisions. The coefficients on the interactions are nearly identical, suggesting that learning is ongoing.

Columns 4 and 5 investigate whether the effect of a surprise in a movie's performance depends on whether the surprise is positive or negative. Column 4 indicates that the increase in the probability of entry due to positive news is more than twice as large in magnitude as the decrease in the probability due to negative news. This is likely due to how the expected revenues are distributed around the entry cutoffs. The result suggests that there is a larger mass of expected revenues within one standard deviation of update below the cutoffs than there is above. Column 5 breaks down the effect of positive and negative updates by quartile of lagged expected log revenue. Negative updates become more salient as the quartile increases. In fact, observations in the first quartile are unaffected by negative updates. Since these observations are unlikely to be associated with a release at all, the negative news does not have an impact. Positive updates have the greatest salience for observations in the middle quartiles. It is in this range that surprise good performances are most likely to push expectations above the entry thresholds.

4.2 Alternative Models

There is an alternative explanation for the main result that "surprise" performances affect further entry. It is probable that firms have information about the quality of their movies that is not captured by the first-stage regression of equation (15). In the extreme, they could know the quality perfectly, in which case any deviation from their expectations would be entirely due to idiosyncratic movie-destination demand shocks. Movies with seemingly big positive surprises would enter more countries in subsequent periods because they are good movies. Distributors would know this from the start and could be delaying for reasons other than learning. The methodology of this paper would erroneously attribute the correlation between "surprises" and entry to learning.

To see whether this is driving the results, we can use the fact that this alternative hypothesis implies that firms can anticipate the surprises from future rounds. If no learning was taking place, substituting the update from the current period (which isn't observed before current-period entry decisions are made) should produce similar results to including the lagged update. If the significance of the lagged update is due entirely to

Table 3: Probability of Exporting to a New Market

model	(1)	(2)	(3)	(4)	(5)
depvar	released	released	released	released	released
pred. $\ln R$	0.148***				
	(0.006)				
lag pred. $\ln R$		0.144***	0.144***	0.148***	
		(0.006)	(0.006)	(0.006)	
lag update		0.050***			
		(0.003)			
per. 2 lag update			0.0514***		
			(0.004)		
per. > 2 lag update			0.0489***		
			(0.005)		
negative update				0.0321***	
				(0.004)	
positive update				0.0730***	
				(0.007)	
lag pred. Q1 (d)					-0.191*
					(0.080)
lag pred. Q2 (d)					-0.0624
					(0.080)
lag pred. Q3 (d)					0.0604
					(0.080)
lag pred. Q4 (d)					0.168*
					(0.080)
neg. update × pred Q1					0.0089
					(0.012)
neg. update × pred Q2					0.0372***
					(0.009)
neg. update × pred Q3					0.0402***
					(0.007)
neg. update × pred Q4					0.0474***
					(0.009)
pos. update × pred Q1					0.0501***
					(0.010)
pos. update × pred Q2					0.0695***
					(0.010)
pos. update × pred Q3					0.0671***
					(0.010)
pos. update × pred Q4					0.0542***
					(0.012)
N	24251	24251	24151	24251	24151
pseudo R^2	0.129	0.131	0.131	0.132	0.121

Standardized average partial effects; robust standard errors are adjusted for clusters in movies
(d) for discrete change of dummy variable from 0 to 1
* $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

learning, then the current-round update should not enter significantly. The first column of Table 4 estimates the effect of current expected log revenues on the probability of entry. The difference from column 1 of Table 3 is that first-round observations are included in the regression. This is to act as a benchmark for the specification of column 2, which includes the current predicted log revenue and the update derived from current entries. Column 2 indicates that a one-stand-deviation increase in the current update increases the probability of entry by 0.85 percentage points. This suggests that firms do have some information not accounted for in the initial forecast equation, but the estimated effect is about one-sixth of the estimate for lagged updates, which is reproduced in column 3 for convenience. The fact that the effect of lagged updates is so much stronger than current (unrealized) updates suggests that we should not abandon the learning hypothesis.

In column 4, the variance of the prior distribution of log revenues is included. Recall from equation (14) of section 3 that we expect the variance to enter positively. Mechanically, this is because the logarithm of the expected revenue is the expected log revenue plus one half the variance of log revenue if revenue is distributed log-normally. Intuitively, firms prefer to enter when the variance is high because their potential losses are capped by the entry cost but there is no bound on the up side. Thus the combination of the assumption of risk-neutral preferences on the part of firms and log-normally distributed conditional revenues provides the hypothesis that the variance term should enter positively. Column 4 of Table 4 shows that high-variance observations are actually less likely to be associated with entry. There are a couple of possible explanations to this finding. First, firms may in fact be risk averse. Goettler and Leslie (2004) note that industry-insiders claim to treat risky movies differently in their study of cofinancing in the motion picture industry. In that paper, it is the studios' decisions of how to finance the movies' production that is at issue. The authors point out that risk-averse behavior is not expected for publically-owned firms, since shareholders can diversify risk through

Table 4: Probability of Exporting to a New Market

model	(1)	(2)	(3)	(4)
depvar	released	released	released	released
pred. $\ln R$	0.166***	0.166***		
	(0.006)	(0.006)		
current update		0.00852**		
		(0.003)		
lag pred. $\ln R$			0.144***	0.120***
			(0.006)	(0.005)
lag update			0.0504***	0.0422***
			(0.003)	(0.003)
variance $\ln R$				-0.165***
				(0.010)
N	34144	34139	24251	24251
pseudo R^2	0.134	0.135	0.131	0.150

Standardized average partial effects

Robust standard errors adjusted for clusters in movies

* $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

their portfolio. Lambart (1986) argues that risk-averse behaviour could be explained by agency issues with risk-averse managers. Adding risk aversion to the present model would only strengthen the desire of distributors to learn their movie's quality before committing to foreign entry. I therefore leave such considerations outside the model. Second, recall that the model of section 3 does not explicitly take into account the informational value of entry. Entering when the prior variance is high would be less valuable in this respect because the firm could not infer as much about quality as it could if the variance is low. This is because surprises could be due to large idiosyncratic shocks rather than high or low quality. Thus, the informational component of the value of entry would lead to firms favouring low-variance markets, as the empirical results suggest.

5 Conclusion

A growing body of work has suggested that manufacturing firms learn about their export profitability through exporting. This paper adds to that literature by considering a new type of product. Motion picture distributors only release a movie once in any destination country, and thus have limited scope for intra-market learning. Furthermore, potentially large idiosyncratic differences in taste across markets mean inferences from observed performance must be far from perfect. Nonetheless, the results of this study suggest that distributors do adjust their entry strategies based on prior-market performance, adding markets after surprise successes and limiting further distribution after disappointments.

The correlation between past surprises and entry decisions could be due to omitted movie attributes in the initial forecasts. Movies with positive unobserved attributes will both perform better than expected (by the econometrician) and subsequently enter more foreign markets. Robustness checks suggest this is likely a factor, but unrealized surprises' effect on entry decisions is just one-sixth the size of past surprises, leading to the conclusion that learning is indeed taking place.

One limitation of this study is that the information value of delaying entry is not explicitly modeled, nor accounted for in the empirics. Prior theoretical work has modeled this option value, but these studies have relied on other simplifications to make modelling trackable. Simplifications include limiting the analysis to two countries (Albornoz et al., 2010), limiting uncertainty to a binary distribution (Akhmetova, 2010), or restricting the correlation of demand between countries to be equal across country-pairs (Nguyen, 2012). Indirect evidence of strategic delay is found in the present study by inspecting the effect of prior distribution variance on entry decisions. Risk-neutral firms prefer high variance if entry is made myopically because their losses are capped at the cost of entry but there is no bound on the up side. However, if firms use entry to learn about demand in potential future destinations, lower variances provide a higher information value. Empirical results suggest the latter effect to be at work.

As firms move toward a simultaneous release strategy to combat international piracy, they lose the ability to use the information from prior markets. Thus, firms face a trade-off between foregone revenues to illegal consumption if they delay foreign entry on the one hand, and potentially loss-making foreign entries if they enter all markets simultaneously on the other hand. Firm behavior is consistent with this trade-off: big-budget movies which are likely to draw higher box-office returns are much more likely to enter foreign markets simultaneously than smaller-budget movies that could be on the cusp of the break-even point.

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